

Neurocognitive Mechanisms of Type 1 and Type 2 Decision Making Processes

by

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Abstract

In an attempt to understand how humans make decisions, a wealth of researchers have explored the commonalities of different decision making demands. Two ranges of systems have been classified. Whereas Type 1 decision making is fast, automatic, and effortless, Type 2 judgments are slow, contemplative, and effortful. Here, I sought to determine underlying mechanisms of these processes. To do this, I present an extensive review and two electroencephalogram experiments. My review addresses theoretical models defining Type 1 and Type 2 decision making, discusses the debate between dual-process and continuous frameworks, proposes a novel insight into how these processes are selected and executed, and outlines neuro-anatomical findings. In one experiment, participants retained digits (Type 1 processes) and completed mathematical computations (Type 2 processes). I found that cognitive control – as reflected by frontal theta – and attentional mechanisms – as reflected by parietal alpha – are core mechanisms in Type 1 and Type 2 decision making. In a second experiment, I sought to replicate these findings when trained students diagnosed diseases. Differences in theta and alpha activity were not seen. I posit that the discrepancy between experiments may be because cognitive control relies on uncertainty which existed in experiment one but not experiment two. Moreover, attentional mechanisms involve the retrieval of knowledge in which the demands would have differed in experiment one but not two. I conclude by describing how cognitive control and attention fit into my hypothesis of different decision making steps: process selection and execution. These findings are important as they could lead to the assessment of decision making processes in real-world contexts, for example with clinicians in the hospital. Moreover, they could be used in biofeedback training to optimize decisions.

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CHAPTER ONE: THE DUAL-PROCESS VERSUS CONTINUOUS DEBATE: A REVIEW OF TYPE 1 AND TYPE 2 THEORETICAL MODELS

1.1. Introduction

Decision making ranges from simple to complex. For instance, we can easily decide which route to take to work but not in a foreign country. Intuitively we know $2 + 2$ equals 4, yet take much more effort to determine that 137×14 equals 1918. In cognitive psychology, these decision making processes are broadly described as Type 1 and Type 2, respectively (formerly System 1 and System 2; see Evans, 2006). Research has defined Type 1 decision making processes to be fast, associative, and effortless and Type 2 decision making processes to be slow, contemplative, and effortful (e.g., Stanovich & West, 2000). More recently, they have been linked to working memory (Evans & Stanovich, 2013a), attention (Kruglanski & Gigerenzer, 2011), cognitive control (Kahneman, 2011), and rule-based mechanisms (Kruglanski & Gigerenzer, 2011). Within this literature, however, there is a debate as to whether Type 1 and Type 2 decision making reflects two discrete processes (dual-process theories) or two extremes of a single continuum (continuous theories).

In terms of a lightbulb, a dual-process framework is analogous to a toggle switch, whereas a continuous framework is to a dimmer switch. The former either employs Type 1 or Type 2 processes while the latter can recruit degrees of both. As human decision making is more complex than a light switch, there exists multiple theoretical models as to how each of these processes operate (see Table 1). Within the dual-process framework, some researchers argue that Type 1 processes first occur but may be overridden by Type 2 processes. Others provide a different account by positing that Type 1 and Type 2 decision making processes are in competition and can occur in parallel (Barbey & Sloman, 2007; Smith & DeCoster, 2000).

Within the continuous framework, theorists have described models with a single dimension (Kruglanski & Gigerenzer, 2011), but also three dimensions (Varga & Hamburger, 2014). A tension has arisen between proponents of these different models. Specifically, Keren (2013) and others (Keren & Schul, 2009) have argued that dual-process theories of Type 1 and Type 2 decision making are ambiguous, do not motivate any scientific advancements, and are untestable. Evans and Stanovich (2013b) agreed with this but posited their use in stimulating high-level ideas. Although continuous models have not been criticized in the same way, they are susceptible to the same shortfalls (Evans & Stanovich, 2013a).

Table 1. A comparative table describing the mechanisms involved in Type 1 and Type 2 decision making for four theoretical models across two frameworks. It is important to note the tri-dimensional model does not directly signify between Type 1 and Type 2, thus we here simplified this model in order to better compare with other models

Framework	Model	Type 1	Type 2
Dual-Process	Default Interventionist (Evans & Stanovich, 2013a)	Autonomous	Working memory, mental simulations, cognitive decoupling
	Emulation-Based Framework for Cognition (Colder, 2011)	Sensory and motor processes	Goal setting and maintenance processes
Continuous	Unified Theory of Judgment (Kruglanski & Gigerenzer, 2011)	Easy rules	Difficult rules
	Tri-Dimensional (Varga & Hamburger, 2014)	Quick, effortless, lack of control	Slow, effortful, controlled

This article provides a comprehensive review of theoretical models that describe Type 1 and Type 2 decision making and the debate between dual-process and continuous accounts. Additionally, we propose a novel dissociation of decision making steps across Type 1 and Type

2 processing. We conclude by exploring the neural underpinnings of dual-process and continuous models to bring light to how this may occur within the brain.

1.2. Dual-Process Models

Dual-process systems are defined by antonyms: automatic and controlled, nonconscious and conscious, associative and rule-based (e.g., Sanfey & Chang, 2008; Stanovich & West, 2000). Early dual-process theories distinguished Type 1 and Type 2 decision making using these and other qualities (i.e., Kahneman, 2003; Stanovich, 1999; Stanovich, 2005; Stanovich & West, 2000). For example, Type 1 decision making was described as associative, implicit, intuitive, fast, effortless, and non-conscious while Type 2 decision making as rule-based, explicit, analytical, slow, effortful, and conscious (Stanovich & West, 2000). In contrast to labeling each decision making process as a list of qualities, Evans and Stanovich (2013a) defined them as the recruitment of working memory.

Specifically, they proposed that Type 1 decision making did not need working memory mechanisms, but Type 2 decision making did. Evidence in support of this came from research inducing time constraints (Gillard, Van Dooren, Schaeken, & Verschaffel, 2009; Roberts & Newton, 2001), working memory load (Gillard et al., 2009; Roberts & Newton, 2001), and cognitive load (De Neys, 2006; Gillard et al., 2009). For example, De Neys (2006) had participants complete a reasoning task under various degrees of cognitive load. In this study, participants completed syllogisms within which logic was congruent (no-conflict) or incongruent (conflict) with prior beliefs. Superimposed onto this task was the need to remember a pattern of dots which were organized in complex (high-load) or simple (low-load) patterns. If the dual-process account of decision making held true, the no-conflict condition would require Type 1 decision making without working memory, while the conflict condition would recruit Type 2

decision making and working memory. Consequently, the high-load condition would affect the conflict (Type 2) but not the no-conflict condition (Type 1). Indeed, in contrast to the low-load condition De Neys (2006) found that the high-load condition impaired performance for Type 2 decisions but not for Type 1 judgments.

Evans and Stanovich (2013a) added that Type 1 decision making involves autonomous processing while Type 2 decision making entails cognitive decoupling (see also Stanovich & Toplak, 2012). Thompson (2013) described autonomy as a mental representation of both the question and the answer. In terms of the problem '2 + 2', it is now represented in our minds as '2 + 2 = 4'. In contrast, non-autonomic (Type 2) decision making requires hypothetical reasoning and cognitive simulations – the ability to reach various possible outcomes to select the best course of action (Evans & Stanovich, 2013a). Being able to distinguish these simulations from the real-world is called cognitive decoupling (Evans & Stanovich, 2013a; Stanovich & Toplak, 2012). This ability has been demonstrated in the theory of mind (e.g., Leslie, 1987) and motor control literature (e.g., Miall & Wolpert, 1996). Even with working memory, cognitive decoupling, and autonomy as the core of these decision making processes, a question still remains: in what conditions do we make Type 1 or Type 2 decisions?

Kahneman (2011) and others (Evans & Stanovich, 2013a; Kahneman & Frederick, 2002) have posited the *default interventionist model*: a model whereby Type 2 decision making imposes its influence onto Type 1 decisions. Kahneman (2011) proposed that Type 1 is the first and main operator of the brain. When a Type 1 response is inadequate, however, Type 2 enforces its control. For example, when walking by the cookie jar, our first impulse might be to eat a cookie, yet we may stop ourselves if we are on a diet. For Type 2 decision making to override Type 1 decisions, there must be a combination of difficulty, novelty, and motivation (Evans &

Stanovich, 2013a). Moreover, to suppress the default response involves attentional mechanisms (Stanovich & Toplak, 2012). The capability of Type 2 decision making to do this has been demonstrated in research on executive functioning (Aron, 2008; Best, Miller, & Jones, 2009; Bourgeois-Gironde & Van Der Henst, 2009; De Neys et al., 2013; Frederick, 2005; Hasher, Lustig, & Zacks, 2007).

Thompson (2013), however, questioned claims that the purpose of Type 2 decision making is to suppress Type 1 responses (Shynkaruk & Thompson, 2006; Thompson, Prowse Turner, & Pennycook, 2011; Thompson et al., 2013). Addressing this, Shynkaruk and Thompson (2006) allowed participants to review their past rapid judgments and urged them to do so contemplatively. They found that participants often retained their original response. This indicated that Type 2 decision making processes could be recruited without overriding Type 1 responses. Evans (2011) refined the default interventionist model in a way that may help explain these findings. He indicated that Type 1 decision making computes a 'default' decision and Type 2 decision making *always* assesses whether to override. Dependent on the necessary cognitive effort, a decision is reached. Important characteristics of this model include that Type 1 and Type 2 processes are serially organized, that Type 1 decision making processes must complete prior to Type 2 decision making processes, and that both types of decision making are involved in all decisions.

There are other models, however, that approach the relationship between Type 1 and Type 2 processes in a different way. The *parallel-competitive model* (Barbey & Sloman, 2007; Smith & DeCoster, 2000) posits that Type 1 and Type 2 decision making occur simultaneously and in competition. Specifically, both decision making processes provide a response and one is selected. Some have argued, however, that this is not in line with theoretical frameworks that

underlie dual-process theory (Evans & Stanovich, 2013a). For example, for two competitive systems to exist, both types of processing must complete prior to making a decision (Evans & Stanovich, 2013a). Moreover, this model offers that Type 2 decision making always occurs - making every decision effortful (Evans & Stanovich, 2013a). Alternatively, the *emulation-based framework for cognition* (Colder, 2011) theorizes that parallel processing between Type 1 and Type 2 decision making occurs in cooperation and have different functions. Type 1 decision making is necessary for short-term navigation of the immediate environment, relying on sensory and motor processing. This is confirmed in the motor control literature where movements are, in part, mediated by forward models (Desmurget & Grafton, 2000; Wolpert & Ghahramani, 2000; Wolpert & Kawato, 1998). Forward models integrate motor plans with sensory input to evaluate, adjust, and optimize movements. Type 2 decision making, on the other hand, is concerned with long-term goals. Recent developments in the reinforcement learning literature have confirmed this dissociation (Ribas-Fernandes et al., 2011; Ribas-Fernandes, Shahnazian, Holroyd, & Botvinick, 2018). Particularly, Ribas-Fernandes and colleagues (2018) found that neural learning mechanisms are hierarchically organized and that high-level goals may be separable from lower-level subgoals. Further, Ribas-Fernandes and colleagues (2011) concluded that this was distinct from perceptual and motor processing. In other words, Type 2 decision making maintains long term goals (e.g., driving to the market) while Type 1 decision making addresses immediate and changing environments (e.g., the traffic light turning yellow).

The dual-process account of Type 1 and Type 2 decision making is popular. Although the default-interventionist model is the most popular theoretical model, others exist which have considerably different approaches to the dual decision making processes, as outlined above.

These competing models demonstrate a tension that exists within this field of research which is further complicated by the rise of continuous models, as described in the next section.

1.3. Continuous Models

Dual-process models of Type 1 and Type 2 decision making dominated research for a significant amount of time, however, a growing research literature now contends that these decision making processes are governed by the same decision making network (Bargh, 1994; Bargh & Morsella, 2008; Gigerenzer & Regier, 1996; Keren, 2013; Keren & Schul, 2009; Kruglanski, 2013; Kruglanski & Gigerenzer, 2011; Melnikoff & Bargh, 2018; Osman, 2004; Osman, 2013; Varga & Hamburger, 2014; Zbrodoff & Gordon, 1986). Whereas dual-process accounts posit two distinct decision making processes (i.e., one for Type 1 and one for Type 2), continuous accounts posit a single process within which decisions that resemble Type 1 or Type 2 are evoked. Thus, decision making is graded in that one may operate quickly and automatically (Type 1), slowly and controlled (Type 2), or in a manner that falls somewhere in-between. There are many researchers that argue against dual-process theories (Bargh, 1994; Bargh & Morsella, 2008; Gigerenzer & Regier, 1996; Keren, 2013; Keren & Schul, 2009; Kruglanski, 2013; Kruglanski & Gigerenzer, 2011; Melnikoff & Bargh, 2018; Osman, 2004; Osman, 2013; Varga & Hamburger, 2014; Zbrodoff & Gordon, 1986), and a few that have modelled Type 1 and Type 2 decision making in a continuous manner (Kruglanski & Gigerenzer, 2011; Varga & Hamburger, 2014). These models were built to explain human behaviours and cognition comparably to dual-process accounts, yet in a simpler way.

A continuous *unified theory of judgment* model was proposed by Kruglanski and Gigerenzer in 2011. This model was stimulated by their belief that both Type 1 and Type 2 decision making are rule-based rather than Type 1 being associative and Type 2 being rule-based

as originally proposed (Stanovich & West, 2000). Kruglanski and Gigerenzer (2011) described ten heuristic-based (Type 1) rules – shortcuts that focus on certain information in order to simplify the problem at hand. For example, the scarcity heuristic is a tendency to attribute a higher value to an item if it is rare (Parker and Lehman, 2011; Williams, Saffer, McCulloch, & Krigolson, 2017). Parker and Lehman (2011) found that when deciding between two types of equally priced wine, participants more often chose the wine that was scarce rather than abundant. Evidence has, however, demonstrated that intuitive rules can also be applied in deliberative (Type 2) judgments (Kruglanski & Gigerenzer, 2011). When encountered with a problem, perceptual and memory mechanisms first select potential rules (e.g., if it is rare then it is more valuable) that are applicable and may achieve a solution (Kruglanski & Gigerenzer, 2011). This process results in a ‘consideration rule set’ from which a rule will be selected and applied.

The selection of a rule depends on each rule’s probability of success and difficulty to apply which is contrasted to one’s attentional capacity and motivation (Kruglanski & Gigerenzer, 2011). Additionally, these rules exist on a continuum where they vary from easy to difficult depending on routinization (experience) and accessibility (memory). Consequently, the ability to apply this range of rules relies on processing potential (attentional capacity and motivation) in that potential is positively associated with the rule difficulty that can be applied. In other words, with low potential we can only apply easy rules but with high potential we can apply a range of rules from easy to difficult. As this set of rules is originally acquired rapidly via memory mechanisms, it can be biased (e.g., by priming) and result in an incomplete and/or inadequate list (Kruglanski & Gigerenzer, 2011). If no rule is deemed adequate, we can spend cognitive resources to re-recruit memory mechanisms to better populate the list of rules. Ultimately, a rule will be selected and applied resulting in a solution.

The unified theory of judgment is not the only continuous approach that may be implemented, however. Varga and Hamburger (2014) described a model that sought to complete goals by depending on three processing continuums: speed, effort, and control. Speed refers to the time taken to reach a decision, effort is defined as working memory and computational capacities, and control can vary from automatic to deliberate. Although their *tri-dimensional* model followed the same rule-based principles as Kruglanski and Gigerenzer (2011), they expressed concerns about limiting decision making to a single continuum. They posited that having multiple continuums opens the way to better explain a larger set of complex decisions.

To date, there exists less continuous models than dual-process models that explain human decision making. None-the-less, the variety of models described adheres to the disagreement between theorists. It's then as important to discuss the debate that has arisen within this field as it is to examine each model in themselves.

1.4. The Debate Between Dual-Process and Continuous Models

The distinction between dual-process and continuous theories have important implications. In a dual-process framework, Type 1 and Type 2 decision processes are mutually exclusive. Conversely, in a continuous framework Type 1 and Type 2 decision processes reflect the extremes of a decision making continuum that encompasses decisions that look like Type 1, Type 2, or some degree of both. Although dual-process models have existed for a significant period of time, this hasn't been without criticisms (Bargh, 1994; Bargh & Morsella, 2008; Gigerenzer & Regier, 1996; Keren, 2013; Keren & Schul, 2009; Kruglanski, 2013; Kruglanski & Gigerenzer, 2011; Melnikoff & Bargh, 2018; Osman, 2004; Osman, 2013; Varga & Hamburger, 2014; Zbrodoff & Gordon, 1986).

One line of criticism against dual-process theories is addressing the defining characteristics (Bargh, 1994; Bargh & Morsella, 2008; Kruglanski & Gigerenzer, 2011; Shae & Firth, 2016; Melnikoff & Bargh, 2018; Zbrodoff & Gordon, 1986). An assumption has risen: all defining factors (e.g., Type 1 is fast, automatic, and effortless while Type 2 is slow, contemplative, and effortful) must always occur together and exclusively from those of the opposing decision making process (Keren & Schul, 2009). Research has demonstrated that the set of attributes defining each of the decision making processes do not always occur together (Bargh, 1994; Bargh & Morsella, 2008; Keren & Schul, 2009; Melnikoff & Bargh, 2018; Zbrodoff & Gordon, 1986), and more importantly that attributes across the two decision making processes are not mutually exclusive (Bargh, 1994; Bargh & Morsella, 2008; Eitam, Hassin, & Schul, 2008; Eitam, Schul, & Hassin, 2009; Hassin, 2005; Keren, 2013; Keren & Schul, 2009; Feldman Barret, Ochsner, & Gross, 2007; Melnikoff & Bargh, 2018; Zbrodoff & Gordon, 1986). For example, Kruglanski and Gigerenzer (2011) advocated that both types of decision making are rule-based (see also Varga & Hamburger, 2014). Similarly, Shae and Firth (2016) argued that they are both conscious. In response to these criticisms, Evans and Stanovich (2013a) argued that these descriptive characteristics should no longer operationally define the decision making processes, but are rather correlated with them.

Based on this assertion, Evans and Stanovich (2013a) put forth new definitions for Type 1 and Type 2 decision making - Type 1 decision making is autonomous and does not require working memory, whereas Type 2 decision making relies on working memory and cognitive decoupling. Regardless, Kruglanski (2013) and Keren (2013) continued to argue that there were still no clear operational definitions of autonomy, working memory, or cognitive decoupling. Moreover, researchers have indicated that working memory (Type 2) is a continuous mechanism

in itself and question how this could be incorporated into a dual-process model (Thompson, 2013). In line with this, Kruglanski (2013) signified that autonomy (Type 1) also lies on a continuum. That each of these mechanisms are in themselves a continuum is a strong argument for those who advocate for a continuous account as it is difficult to distinguish where the borders of each decision making process lie. Interestingly, dual-process theorists have since agreed that both Type 1 and Type 2 processes are continuums, yet propose that each process does not operate as if they are all-or-none (Evans, 2010; Evans & Stanovich, 2013a, 2013b). Evans (2010) discussed ‘cognitive modes’ to be various cognitive styles that exist within Type 2 decision making. These modes exist on a continuum and may be influenced by the internal and external environment, personality, and personal history (Evans, 2010; Evans & Stanovich, 2013a). Additionally, Evans and Stanovich (2013b) have agreed that autonomous decision making varies as a factor of stimulus accessibility. This means that both Type 1 and Type 2 decision making exist on distinct continuums, yet it is still unclear as to whether any of the provided evidence is sufficient to detach them from each other.

Keren (2013) indicated that Evans and Stanovich’s (2013a) evidence for their model was selective and only drew from research that supported their claims. Furthermore, Kruglanski (2013) depicted that much of the evidence put forth by Evans and Stanovich (2013a) focused on one or two anatomical regions, despite their claim that the difference between Type 1 and Type 2 decision making should be across different neural networks. These issues arose because the development of dual-process models was built upon literature from other psychological fields (e.g., working memory). Much of this evidence broadly demonstrated functional dissociations between processes, leaving room for subjectivity and speculation (Evans & Stanovich, 2013a, 2013b; Kruglanski, 2013; Kruglanski & Gigerenzer, 2011; Keren, 2013; Osman, 2013;

Thompson, 2013). Functional dissociations are categorized as single or double. Single dissociations are when a variable affects one task but not another (Dunn & Kirsner, 1988). A double dissociation is when one variable affects Task A but not Task B and another variable affects Task B and not Task A. It has been shown, however, that dissociations are not adequate evidence to determine whether decision making processes fit within a continuous or dual-process model (Dunn & Kirsner, 1988). Even though Dunn and Kirsner (1988) described an empirical method, the reverse association assessment, to determine whether a phenomenon is composed of a continuous process or dual-processes, none of the aforementioned models have applied this technique to their supporting evidence.

A reverse association assessment can be conducted by first transforming the data across two tasks (although the details of this transformation is beyond the scope of this article, the process is described in Dunn & Kirsner, 1988). Any dependence between all variables, processes, and tasks within a comparison (e.g., Type 1 and Type 2 decision making) becomes contingent on whether the transformed data is monotonic or not. If this reveals any dependence (it is monotonic), a continuous model cannot be rejected. Alternatively, if independence is met (it is not monotonic), then a continuous model is rejected and a dual-process (or multi-process) model is adopted. As none of the models discussed in this article have assessed whether the data presented in support for their model holds a reversed association, the evidence presented is speculative and subject to misinterpretation. Future research must address this question empirically by applying this technique.

These criticisms have brought the field of decision making to an impasse. To advance our knowledge, it is necessary to progress these models and make them testable. First, all constructs must be precisely operationally defined. This will allow for a clear understanding of the involved

mechanisms, and open way for the development of computational models. Second, dual-process models must create clear boundaries as to where one type of decision making ends and where the other begins while continuous models must be explicit as to how degrees of each may be recruited. Lastly, when advocating for either a continuous or dual-process model, it is necessary to empirically test the supporting evidence to extinguish speculation and misinterpretation.

1.5. A Novel Insight of Process Selection and Execution

Within this review, we have highlighted many similarities that exist across models. A novel insight that we propose is that there are at least two steps to Type 1 and Type 2 decision making (see Table 2). The first of which is process selection: where a decision making process (Type 1, Type 2, or somewhere on the continuum) is adopted. Whereas within the default interventionist model, this is described as an evaluation as to whether Type 2 decision making should override Type 1 decisions (Evans & Stanovich, 2013a), in the unified theory of judgment this is engrained in the rule-selection process (Kruglanski & Gigerenzer, 2011). The second step is process execution: where one must implement the selected decision making process in order to achieve a solution. This may take the form of working memory (Evans & Stanovich, 2013a) or rule-following processes (Kruglanski & Gigerenzer, 2011). These steps are automatic and engrained within Type 1 and Type 2 decision making processes.

Within the default interventionist model, the process selection stage is governed by an evaluation of difficulty, novelty, and motivation (Evans & Stanovich, 2013a). Unfortunately, this claim was brief and they did not explain how this occurs. The unified theory of judgment (Kruglanski and Gigerenzer, 2011), on the other hand, focused the majority of their discussion on process selection in that they described that how much effort to employ (where on the Type 1 – Type 2 continuum) is dependent on different rules' probability of success (ecological

rationality), rule difficulty, attentional capacity, and motivation. What is consistent with these models is an evaluation of task demands and internal capabilities. Thus, it seems that each model might agree as to what factors result in an adopted decision making process. However, there is a difference in that dual-process models would assume this decision is based upon a threshold which, if surpassed, would recruit Type 2 decision making. Alternatively, the continuous models would utilize this computation to direct the degree to which Type 2 decision making is recruited.

When considering the step of process execution, Evans and Stanovich (2013a) described this step in detail while Kruglanski and Gigerenzer (2011) simply described it to be rule-following mechanisms. Specifically, the default interventionist model posited that Type 2 decision making requires working memory, mental simulations, and cognitive decoupling, while Type 1 decision making is autonomous. What's interesting is that working memory and rule-guided behaviour are highly intertwined (Amso, Haas, McShane, & Badre, 2014). The working memory mechanism that has been posited by Evans and Stanovich (2013a) is broad thus may (and likely does) involve rule-guided mechanisms. Furthermore, there is research demonstrating that rule-selection and following depend on working memory (Amso et al., 2014). Thus, it is unclear whether the proposed rule-following (Kruglanski & Gigerenzer, 2011) and working memory (Evans & Stanovich, 2013a) mechanisms are truly dissociable. That said, this is an important point in which the theories differ in that dual-process models need not always recruit these mechanisms, while continuous models would claim that these mechanisms are always recruited yet to varying degrees.

What becomes clear with the dissociation of these decision making steps is that each of these popular models focuses on different aspects of Type 1 and Type 2 decision making. Whereas the unified theory of judgment focused on process selection, the default interventionist

model focused on process execution. It is necessary for future models to ensure that both of these steps are properly accounted for. In summary, Type 1 and Type 2 decision making first depends on a comparison of external demands (task and rule difficulty) and internal capabilities (attentional capacity, motivation) to select a decision making process. Next, higher-level mechanisms such as working memory may be utilized to execute the selected process via rules and mental simulations. Although this does not in itself answer the continuous versus dual-process debate, it may aid future models or refinements of current models to develop.

Table 2. A comparative table illustrating the mechanisms of the most popular dual-process and continuous models in each step of Type 1 and Type 2 decision making.

Model	Process Selection	Process Execution
Default Interventionist (Evans & Stanovich, 2013a)	Task difficulty, task novelty, and motivation	Autonomy, working memory, mental simulations, cognitive decoupling
Unified Theory of Judgment (Kruglanski & Gigerenzer, 2011)	Ecological rationality, memory, rule difficulty, attentional control, and motivation	Rule-following mechanisms

1.6. Neural Basis of Type 1 and Type 2 Decision Making Models

While the debate between dual-process and continuous decision making models continues from a theoretical perspective, concurrent research in neuroscience has begun to probe the underlying neural mechanisms of Type 1 and Type 2 decision making. We will here review neural literature in two ways: 1) we will investigate the neural underpinnings of cognitive mechanisms as derived by the aforementioned theoretical models, and 2) we will draw from literature that assesses these decision making processes as networks that exist across the brain.

1.6.1. Neural Basis of the Default Interventionist Model

Evans and Stanovich (2013a) proposed that an underlying working memory mechanism differentiates Type 1 and Type 2 decision making. Further in line with this is their claim that Type 2 decision making also depends on mental simulations and cognitive decoupling. Due to the high-level capabilities of Type 2 decision making, it is unsurprising that the locus has been demonstrated in the prefrontal cortex, a region involved in reasoning, planning, and executive functioning (D'Esposito, Postle, & Rypma, 2000). This has further been narrowed to the lateral prefrontal cortex (LPFC) where Funahashi, Bruce, and Goldman-Rakic (1989) recorded single cells of monkeys while they performed an oculomotor delayed-response task. In this task, monkeys were to stare at a fixation cross while a visual cue would briefly appear at a peripheral location. After the offset of the cue, there was a three-second delay, which was followed by a 'go' cue. The monkey was then to look at where the visual cue was presented. For success in this task, the monkey must retain the location of the visual cue in working memory. Funahashi et al. (1989) found that neurons in the LPFC fired above baseline throughout the delay period. What is more interesting, however, is that neural firing either never began or ceased before the go cue in error trials, where the monkey forgot the cue location. Thus, this demonstrated that the LPFC is necessary for holding task-relevant information in working memory and as such may also be a neural region that plays a key role in Type 2 decision making (see also Hruska et al., 2016a).

These initial results have been confirmed in a human model via functional magnetic resonance imaging (fMRI). For example, Courtney, Ungerleider, Keil and Haxby (1997) had participants complete a delayed-matching task. In this task, a face stimulus was presented, followed by an eight second delay and another face stimulus. The participants were to respond as to whether the two faces matched or not. They found that the LPFC was reflective of maintaining the face stimuli in working memory (see also Zarahn, Aguirre, & D'Esposito, 1997). More

current research, however, has demonstrated the LPFC to be a much more complex region than was originally thought (D'Esposito & Postle, 2015). As some have questioned the nature of the LPFC as a region that simply maintains general representations of important information (Lewis-Peacock, Drysdale, Oberauer, & Postle, 2012), a recent study has clarified this regions involvement as the maintenance of *abstract* information (Lee, Kravitz, & Baker, 2013; see also Kravitz, Saleem, Baker, Ungerleider, & Mishkin, 2013; Romero, Walsh, & Papagno, 2006). This locus thus seems to hold many qualities that parallel the conceptualization of Type 2 decision making as proposed by Evans and Stanovich (2013a).

1.6.2. Neural Basis of the Unified Theory of Judgment Model

In the continuous unified theory of judgment proposed by Kruglanski and Gigerenzer (2011), rule-selection was the main mechanism that defined the continuum between Type 1 and Type 2 decision making. Although they indicated that this process is mediated by attentional resources and motivation, the neural locus underlying the selection of rules is likely to deliver more useful information about decision making types. Once again the prefrontal cortex is involved. In a task investigating this, monkeys saw a fixation cross that was one of two colours, indicating whether they were in the 'compound' or 'spatial' condition (White & Wise, 1999). A compound cue built of two shapes and two colours appeared briefly in one of four locations on the screen (left, right, top, bottom) and indicated which of the four locations would be of importance. Four lights then appeared in these locations and, after a delay, one of them dimmed so slightly that it was only noticeable if it was part of central vision. Once the light dimmed, the monkey was to let go of a bar to receive a reward. In the compound condition, the cue itself (and not its location) determined where the light would dim. In the spatial condition, the cue location (and not the cue itself) indicated where the light would dim. Thus in the compound condition, the

monkeys had to utilize complex rules to identify where the cue was indicating, yet in the spatial condition, the monkeys applied simple visually driven rules to identify the correct location. They found that the prefrontal cortex was more active in the compound condition relative to the spatial condition, indicating its involvement in rule processing.

fMRI research with humans have advanced our understanding with how rule-selection is represented within the prefrontal cortex. Crescentini et al. (2011) had participants complete an adapted Brixton Spatial Rule Attainment Task. In this task, participants were presented with an array of 12 circles, one of which was filled in blue. The task was to predict which circle would be blue on the next display dependent on different rules. In this task there were 30 possible rules that varied in difficulty. For example, an easy rule was that the circle always moved by one, while a difficult rule was that the circle moved by one after the first display, two after the second display, and so forth. Within a 'run' (consecutive cards with the same rule) participants were to learn the rule and then follow the rule. In regards to rule processing in the prefrontal cortex, they found activation in the medial prefrontal cortex that extended into the anterior cingulate cortex. Interestingly, while participants were still learning the rule, they found activation in the LPFC. Additionally, Crescentini and colleagues (2011) found a more widespread range of activation including regions within the temporal and parietal cortex. This is in line with animal research findings that demonstrate a distributed network involved in rule-selection including the prefrontal cortex, orbitofrontal cortex, striatum, and parietal cortex (Reverberi, G6rger, & Haynes, 2011). Further, in line with this and claims by Kruglanski and Gigerenzer (2011), Hampshire, Thompson, Duncan, and Owen (2008) hypothesized this to be an adaptable system that is recruited when there is a need for increased executive control.

1.6.3. System-Based Evidence

Thus far we have assessed the neural localization of different theoretical models by focusing on their proposed cognitive mechanisms. Here, we will provide evidence as congruent with network science (Börner, Sanyal, & Vespignani, 2007) which poses that cognition is best represented as distributed networks that span the brain. Using fMRI, Lieberman, Jarcho, and Satpute (2004) sought to determine the neural networks involved in intuition based and evidence based knowledge, paralleling Type 1 and Type 2 decision making. In this study, Lieberman and colleagues (2004) recruited soccer and acting experts and presented them words that fell within a soccer, an acting, and a neutral category. Participants were to indicate whether the word represented them. The researchers hypothesized that words within participants' respective expertise would elicit intuitive-based (Type 1) decisions, while words that were not from their expertise would produce evidence-based (Type 2) decisions. Their findings indicated a dissociation between the types of decisions in that intuitive decisions recruited the ventral medial prefrontal cortex (VMPFC), nucleus accumbens, amygdala, lateral temporal cortex, and posterior cingulate cortex/ precuneus, while evidence based decisions recruited the hippocampus and dorso-medial prefrontal cortex (see also Guida, Gobet, Tardieu, & Nicolas, 2012). Another study investigated how students reacted to moral dilemmas (Green et al., 2004). They found that Type 2, rational decisions elicited greater activation in the dorso-lateral prefrontal cortex (DLPFC), right inferior parietal lobe, and anterior posterior cingulate cortex than Type 1 decisions. Further, when investigating emotionally salient (Type 1) versus non-salient (Type 2) decisions, Goel and Dolan (2003) found that Type 1 decisions revealed increased activation in the VMPFC and right fusiform gyrus, while Type 2 decisions were routed in greater DLPFC activity.

There is also research that examines the overlap of Type 1 and Type 2 decision making, indicating that these networks may not be completely dissociable (see Van Overwalle &

Vandekerckhove, 2013). Rameson, Satpute, and Lieberman (2010) recruited athletes and academics and presented them images and adjectives of each of these and a neutral category. In one task, participants judged images as to the presence or absence of a person in a picture (Type 1 - implicit), and in another task they rated adjectives as to whether it described them or not (Type 2 - explicit). They found that there were overlapping activations in the medial prefrontal cortex, precuneus, ventral striatum, amygdala and a region within the VMPFC and sub-anterior cingulate cortex. Overlapping results were also found by Ma, Vandekerckhove, Van Overwalle, Seurinck, and Fias (2011) who instructed one group of participants to passively read (Type 1) sentences that presented a personal trait of a fictional character and instructed another group to intentionally infer the trait (Type 2). They found that both conditions recruited the temporo-parietal junction and the medial prefrontal cortex. Further research has demonstrated overlap in the dorso-medial prefrontal cortex (Ma et al., 2012) and that level of expertise differentially recruits regions of the prefrontal cortex (Hruska et al., 2016b). Hruska and colleagues (2016b) had novice and expert clinicians diagnose easy (Type 1) and difficult (Type 2) medical cases. They found enhanced activation in the left ventro-lateral prefrontal cortex (VLPFC) when novices made Type 2 clinical decisions in comparison to Type 1 judgments. In contrast, the right VLPFC and DLPFC activity was greater for Type 2 judgments in experts. This indicated a hemispheric dissociation of Type 1 and Type 2 networks across expertise.

1.6.4. Integration and Summary

The cited research depicts that there is certainly overlap and divide between networks when investigating Type 1 and Type 2 decision making. That said, there are many differences in the literature here described and this is due to the nature of the tasks that were used. Whereas some research involved manipulating working memory and rule-following mechanisms, other

research investigated expertise, emotional valence, and social inferences. This makes it difficult to draw concrete conclusions as to whether the overlapping and disparate regions here described are truly part of the Type 1 and Type 2 decision making network/networks or whether they were stimulated by specific task demands. That said, the prefrontal cortex was recruited in all of these studies making it a plausible region involved in Type 1 and Type 2 decision making.

Specifically, it may be that the medial portions of the prefrontal cortex (e.g., VMPFC) are involved in both types of decision making, albeit more strongly for Type 1 decision making, while the lateral portions of the prefrontal cortex (e.g., DLPFC) are more involved in Type 2 decision making. Importantly, these regions are congruent with theoretical models that describe Type 1 and Type 2 decision making (Evans & Stanovich, 2013a; Kruglanski & Gigerenzer, 2011).

1.7. Conclusions

Here, we reviewed theoretical models that were developed to explain Type 1 and Type 2 decision making processes, highlighted the debate between dual-process and continuous perspectives, provided a novel insight as to how we select and execute these processes, and point towards neural findings that widens our knowledge of how humans make decisions. Theorists have argued that characteristics (e.g., fast and reflexive versus slow and contemplative) are no longer adequate in defining these decision making processes (Evans & Stanovich, 2013a), thus models turn to other mechanisms such as working memory (Evans & Stanovich, 2013a) and rule-processing (Kruglanski & Gigerenzer, 2011). There is a divide between models, however, in that they are classified as either dual-process or continuous. Whereas dual-process models posit that Type 1 and Type 2 decision making are discrete, continuous models argue that they are the two extremes of a single decision making operation. This is the core of the debate within the

Type 1 and Type 2 literature. We described this debate in terms of common criticisms and rebuttals that argue for and against each type of model, and caution that the evidence provided for these models need to be examined more closely to truly determine whether they support a dual or continuous framework.

We then provided a novel insight into how Type 1 and Type 2 decision making occurs. Specifically, we posited that there are two steps to decision making: process selection and process execution. The former is composed of mechanisms which determine whether to adopt Type 1 or Type 2 decision making, while the latter involves mechanisms that then solve the problem at hand dependent on the selected process. We determined that the unified theory of judgment continuous model (Kruglanski & Gigerenzer, 2011) was heavily focused on process selection mechanisms while the default interventionist dual-process model (Evans & Stanovich, 2013a) was more descriptive of the process execution mechanisms. Taken together, process selection mechanisms involve a computation between internal and external environments which rely on task demands, internal capabilities, and motivation, while process execution mechanisms rely on higher-level mechanisms such as rule-following, working memory, mental simulations, and cognitive decoupling. Thus, each model must progress by elaborating on the corresponding stage of decision making in which they show a deficit.

We further explored the claims put forth by these models and question whether their main operators (working memory and rule-selection) are, in fact, dissociable. By exploring the possible neural underpinnings of these two models, it appears that these mechanisms are highly intertwined and difficult to dissociate. Additionally, by describing neuroimaging data that focus on Type 1 and Type 2 decision making as a whole, it becomes clear that different regions of the brain are involved for each process, but also that there is overlapping regions shared by both

processes. The convergence of these findings implies that there is a need to modulate and refine current theoretical models in order to better explain what mechanisms are involved and how they interact.

The debate between dual-process and continuous accounts of Type 1 and Type 2 decision making is far from over. This exemplifies the curiosity that we carry and the importance that understanding the rational mind holds. It is clear that we must continue to put forth significant effort into understanding how these different decision making processes operate because they drive our everyday lives. For example, it is interesting to watch a toddler use their full cognitive potential when deciding whether the incentive to eat their broccoli outweighs the cost, while adults can easily drive along a highway with little to no attention. Moreover, it is important to consider what strategies a clinician will use during surgery when they are fresh versus when they are fatigued. Likewise, it is necessary to know how an astronaut will react to an unforeseen emergency as the first human to live on Mars.

CHAPTER TWO: EXPERIMENT ONE – THINKING, THETA AND ALPHA: MECHANISMS OF COGNITIVE CONTROL AND ATTENTION

2.1. Introduction

The decisions we make on a daily basis range from fast, intuitive responses to slow deliberations. For example, while driving on an empty road we rely on automatic control to negotiate corners, stop when required, or follow well known directions. However, while driving on a busy highway we utilize cognitive resources when merging, navigating traffic, or listening to directions from a satnav. These two modes of thinking are broadly classified as Type 1 and Type 2 (Kahneman, 2011; Stanovich & West, 2000), respectively. Whereas Type 1 thinking is fast, automatic, and effortless, Type 2 thinking is slow, contemplative, and effortful (Evans & Stanovich, 2013b; Kahneman, 2011; Kruglanski & Gigerenzer, 2011; Stanovich & West, 2000). Kahneman (2011) described Type 1 as the main operator of the brain that leads to our first impressions, heuristics, and associatively learned responses. However, when deemed necessary, Kahneman (2011) posited that Type 2 interrupts Type 1's automatic processing and exerts control to explore alternative decision options. As this latter mode of thinking requires significant mental effort, we rely on automatic processes whenever possible.

Evidence for two distinct modes of thinking has been thoroughly demonstrated in cognitive psychology (Evans, 2008, 2010; Evans & Stanovich, 2013a). For example, a seminal study by Kahneman and colleagues (Kahneman, Peavler, & Onuska, 1968) demonstrated that performing mathematical computations resulted in an increased processing load through the use of pupillometry. In their work, Kahneman et al. manipulated thinking mode by having participants retain four digits in memory in one condition (Type 1 thinking) or add one to each of the four digits in another condition (Type 2 thinking). They concluded that increased pupil size

in the difficult (adding) condition was analogous to increased processing load. Indeed, pupillometry is purported to be an effective measure of mental effort, and thus an indicator of Type 1 and Type 2 thinking (Kahneman, 2011), given other research (Ahern & Beatty, 1979; Hess & Polt, 1960, 1964) and multiple reviews (Beatty, 1982; Beatty & Lucero-Wagoner, 2000; Mathôt, 2018). With that said, pupil dilation is also modulated by target detection, perception, learning, memory, and decision making thus demonstrating its inability to dissociate underlying cognitive mechanisms involved within automatic and contemplative thinking (Wang & Munoz, 2015). Alternatively, advances in neuroimaging have opened the way to more direct measures of brain activity and thus the underlying cognitive mechanisms.

In the current study, we sought to replicate findings of Kahneman and colleagues' (1968) seminal research and incorporate modern neuroimaging techniques in order to explore the underlying mechanisms that drive Type 1 and Type 2 thinking. We elected to pair pupillometry measures with electroencephalography (EEG) due to their analogous high temporal precision and EEG's more direct association with, and specificity of, brain function. Our decision was also grounded by recent work linking frontal theta activity (oscillations between 4 and 7 Hz) to cognitive control (Cavanagh & Frank, 2014; Cavanagh & Shackman, 2015) and parietal alpha activity (oscillations between 8 and 12 Hz) to attention (Klimesch, 2012; Sauseng et al., 2005) – two of the underlying mechanisms posited by Kahneman (2011) to be differentially recruited during Type 1 and Type 2 thinking. Here, we had participants perform the add-one task (Kahneman et al., 1968) and hypothesized that we would see larger pupil dilations, increased frontal theta activity, and decreased parietal alpha activity when employing Type 2 relative to Type 1 thinking strategies.

2.2. Methods

2.2.1. Participants

Thirty undergraduate students ($M_{\text{age}} = 23$ [95% CI: 21, 25]) from the University of Victoria's Psychology department were recruited through the use of an online sign-up system. One of these participants was removed due to technical issues with data collection. All participants had normal or corrected-to-normal vision, no neurological impairments, and received extra course credit in a psychology course. All participants provided informed consent approved by the Human Research Ethics Board at the University of Victoria (protocol number: 16-428), and the study followed ethical standards as prescribed in the 1964 Declaration of Helsinki.

2.2.2. Apparatus and Procedure

Participants were seated in a sound dampened room in front of a 19" LCD computer monitor with external speakers. As this task required participants to stare at a fixation cross while keeping their eyes open, the room lights were kept on to reduce strain elicited by screen illumination. They comfortably placed their forehead against an eye-tracking mount attached to the table where they were to complete an adaptation of the add-one task as described by Kahneman and colleagues (1968). In the current experiment, we only included the condition in which participants were to verbalize their response (rather than think it). The task was written in MATLAB (Version 8.6, Mathworks, Natick, U.S.A.) using the Psychophysics Toolbox extension (Brainard, 1997) and is available at <http://www.krigolsonlab.com/source-code.html>.

On each trial, participants heard four numbers and were tasked to either simply repeat the numbers that they had heard (add-zero condition), or repeat the numbers after adding one to each of them (add-one condition). For example, if they heard the numbers 4-2-8-5 they would verbalize 4-2-8-5 in the add-zero condition or 5-3-9-6 in the add-one condition. Each trial lasted

26 seconds where the participants stared at a white fixation cross on a light grey background. A 70 dB metronome of 400 Hz sounded for 50 ms in one second intervals (i.e., one beat on each second). On each trial, after two seconds (i.e., two beats of the metronome), the participants heard the instructions ‘say add one’ or ‘say add zero’ where each word was presented on one beat of the metronome. The instructions and numbers presented to participants were created using a neutral man’s voice from an online text to speech website (www.fromtexttospeech.com). After a three second delay, four auditory numbers were presented, one on each of the four proceeding beats. Participants were then to wait for one second before verbalizing their response. They were to verbalize each number, in order, on separate beats of the metronome, thus it took them four seconds. As with the original study (Kahneman, et al., 1968), after they had verbalized their response, they waited for a one second delay, and verbalized the same response again. After four more seconds, the trial ended. During the experiment, participants were instructed to keep their eyes open to facilitate pupil area measures. As this would be difficult for some participants, we emphasized they keep their eyes open from the time they were presented the numbers to when they finished reporting their response. The experiment began with practice trials in order for participants to learn the pattern of the task (e.g., when to respond). Practice trials continued until both the experimenter and participant indicated that they had effectively learned to perform the task. Participants then underwent four blocks of 10 trials within which half were add-one trials and half add-zero trials, presented in random order. Between each block, participants were presented with a self-timed break.

2.2.3. Data Acquisition and Processing

In this study, auditory recordings, pupil area, and EEG data were collected. Auditory recordings were used in post processing to determine whether the participant performed each

trial adequately and correctly. Trials that were deemed inadequate (e.g., did not report their responses in sync with the metronome) or where the participant reported incorrect digits (error trials) were marked in order to remove corresponding pupil and EEG data.

Pupil area data were recorded within MATLAB via an Eyelink II (SR Research Ltd., Ottawa, Ontario, Canada) device that was attached to a custom head mount. Further, all processing was performed within MATLAB. One of the two cameras were used and was placed below the left eye, angled upwards, with a distance so that the entire eye completely filled the width of the camera. Between each trial, an experimenter ensured that the eye was in the camera frame before proceeding. Pupil area data was recorded at 500 Hz. Post-collection data was chunked into one second segments, corresponding to each metronome beat. Error trials were then removed. If a blink was detected within a second, the segment was removed and interpolated using a linear regression (de Gee, Knapen, & Donner, 2014) between the preceding and proceeding seconds. As there are known individual differences of pupil size, participant data was standardized (de Gee et al., 2014). The data were then separated into the two conditions (add-one and add-zero) and all trials were averaged within the corresponding condition and second. A difference of the conditions was also calculated (add-one condition – add-zero condition) for each second. This facilitated grand averages in which each second and condition for all participants were averaged.

EEG data was recorded from 64 electrodes mounted in a standard ActiCAP (Brain Products GmbH, Munich, Germany) layout using Brain Vision Recorder software (Version 1.10, Brain Products GmbH, Munich, Germany). During recording, electrodes were referenced to a common ground, impedances were, on average, kept below 20 k Ω and data was sampled at 500 Hz using the ActiCHamp (Revision 2, Brain Products GmbH, Munich, Germany) with an 8 kHz

antialiasing low-pass filter. A DATAPixx processing box (VPixx, Vision Science Solutions, Quebec, Canada) was used to ensure temporal accuracy.

Post processing was first conducted using Brain Vision Analyzer software (Version 7.6, Brain Products GmbH, Munich, Germany) and then using custom code in MATLAB. Excessively noisy and faulty electrodes were first removed. Data was down-sampled to 250 Hz, re-referenced to averaged mastoid electrodes, and filtered using a dual pass Butterworth filter with a passband of 4 Hz to 6 Hz for the theta analyses and 11 Hz to 12 Hz for the alpha analyses. Epochs spanning 1000 ms prior to and 2000 ms following the onset of the metronome at each second was created to facilitate ocular correction via independent component analysis (ICA). A restricted infomax ICA with classic PCA sphering was used to extract components. Components containing eye blinks were selected manually via component head maps and an examination of the related factor loadings. The artifacts were then removed using ICA back transformation. Electrodes removed early during processing were interpolated using spherical splines. At this stage, data was exported to a MATLAB format. Within MATLAB, data was then reduced to 0 ms to 1000 ms for each second of each condition, and run through artifact rejection where trials with an absolute difference of 200 μV and/or 20 $\mu\text{V}/\text{ms}$ gradient violation were removed. We then conducted a Fast Fourier transform (FFT) using the standard MATLAB function. The output was normalized and resulted in an output with a 1 Hz resolution. The data did not undergo any tapering. The FFT results were averaged for each second in the corresponding conditions (add-zero, add-one). Although broadly grouping frequency bands is common, this may not reflect commonalities in neural processing, thus we determined frequencies of interest by visually inspecting the data. Specifically, we found consistent activity within a subset of theta (4–6 Hz) and alpha (11–12 Hz). Importantly, theta activity is positively associated with cognitive

control while alpha is negatively related to attention. In other words, increased theta represents increased cognitive control, yet increased alpha reflects reduced attention. Data for each second and each condition were then constrained and binned to these theta and alpha frequency bands. For all participants, differences of each second were created by subtracting add-zero trials from add-one trials. Grand averages of each second in each condition were created across participants.

2.2.4. Data Analysis

A two-tailed repeated-measures t-test was conducted on accuracy to determine any difference in performance across conditions. As previously stated, pupil diameter and FFT processing each resulted in two conditional averages (add-one, add-zero) across the 26 seconds. Kahneman (2011) indicated that the effect of processing (i.e., computations in the add-one condition) was most pronounced after hearing the last of the four digits, thus we focused our analyses to this time window (i.e., the one second interval in which they heard the last number). Particularly, we conducted two-tailed repeated measures t-tests for each measure at this time point. Additionally, we conducted correlational tests between pupil area, theta, and alpha to determine any associations between the measures.

2.3. Results

First, we analyzed measures of accuracy and pupil area to determine whether the add-one condition (Type 2) was more difficult than the add-zero condition (Type 1). In the add-one condition (74% [67%, 81%]), performance was worse than in the add-zero condition (92% [89%, 94%]), $M_d = -18\%$ [95% CI: -24%, -11%], $t(28) = 5.79$, $p < .0001$, $d = -1.08$. The pupil area and EEG analyses focused on the time segment in which the last number was presented to the participant – the time point at which the difference between Type 1 and Type 2 processing is at its peak (see Figures 1 and 2; Kahneman, 2011; Kahneman et al., 1968). Our analysis revealed

pupil area was larger for the add-one condition in comparison to the add-zero condition, $M_d = 2.94$ au [2.33 au, 3.54 au], $t(28) = 9.97$, $p < .0001$, $d = 1.85$.

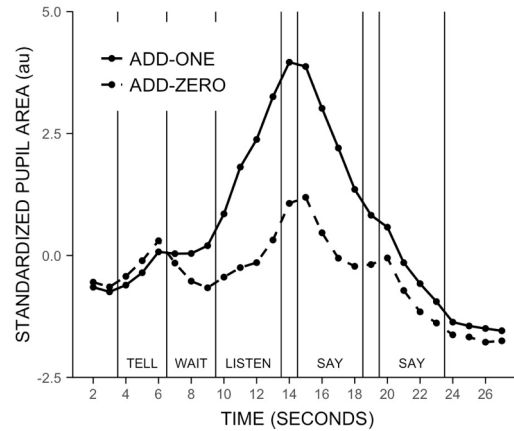


Figure 1. Pupil dilation for both conditions across the task. The x-axis corresponds to one second intervals.

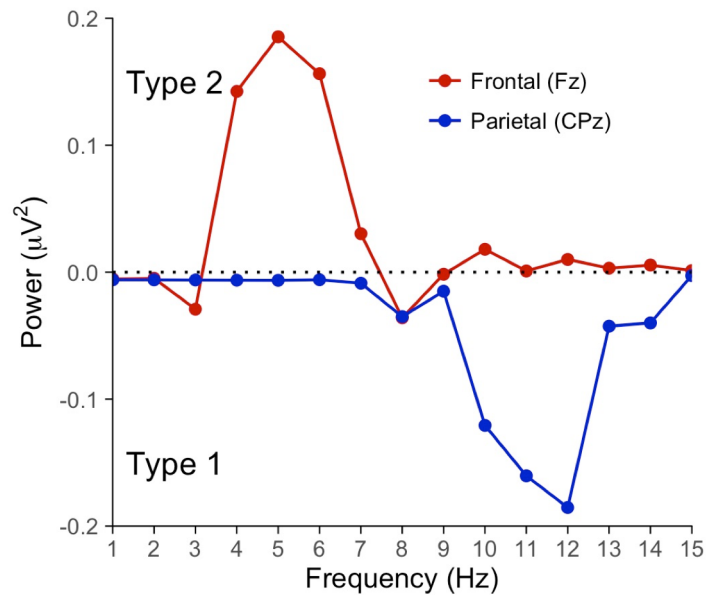


Figure 2. Frequency line plots of the difference between the add-one condition and the add-zero condition for frontal (Fz) and parietal (CPz) electrode locations. Positive values indicate enhanced amplitude for the add-one condition (Type 2 processing) and negative values indicate enhanced amplitude for the add-zero condition (Type 1 processing). Frontal analyses were filtered with a band-pass of 4-6 Hz, while parietal values were filtered with a band-pass of 11-12 Hz.

Next, we investigated whether thinking mode (Type 1 versus Type 2) impacted frontal theta band amplitude and parietal alpha band amplitude. Peak theta and alpha topographic head maps can be seen in Figure 3 – we observed maximal theta amplitude over frontal central regions and maximal alpha amplitude over parietal central regions of the scalp. Frontal theta amplitude (4-6 Hz) was larger for the add-one condition than the add-zero condition, $M_d = 0.16 \mu\text{V}$ [0.04 μV , 0.28 μV], $t(28) = 2.26$, $p = .0315$, $d = 0.42$ at electrode Fz (see Figure 2). Conversely, the add-one condition elicited smaller parietal alpha amplitude at the high range (11-12 Hz) than the add-zero condition, $M_d = -0.17 \mu\text{V}$ [-0.30 μV , -0.04 μV], $t(28) = -2.25$, $p = .0325$, $d = -0.42$ at electrode CPz (see Figure 2). Finally, we investigated whether there were any associations between pupil area, frontal theta amplitude, and parietal alpha amplitude. Correlational scatterplots with trend lines can be seen in Figure 4. Pupil area was positively correlated with theta amplitude, $r(24) = 0.68$, $p = .0001$, and negatively correlated with alpha amplitude, $r(24) = -0.42$, $p = .0345$. Further, theta amplitude and alpha amplitude were inversely related, $r(24) = -0.41$, $p = .0366$.



Figure 3. Topographic headmaps of theta (left) and alpha (right) for the difference between the two conditions (add-one minus add-zero). Each electrode is a pool of up to five electrodes surrounding it. The theta headmap scale ranges from -0.15 μV (blue) to 0.15 μV (red) and the alpha headmap scale ranges from -0.11 μV (blue) to 0.05 μV (red).

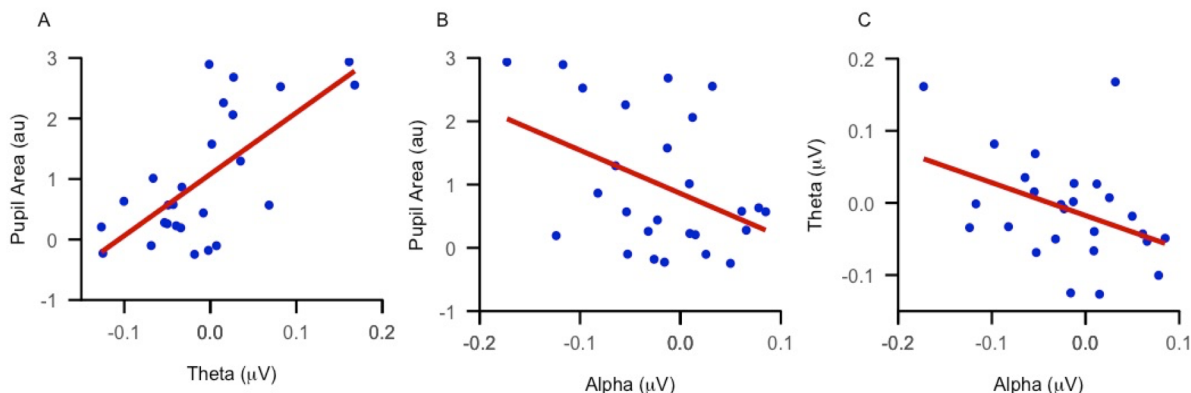


Figure 4. Correlational plots of the difference between the add-one condition and the add-zero condition for each measure indicating relationships between variables. The red line represents a linear trend ($ax + b$) in the data.

2.4. Discussion

Different modes of thinking are subserved by neural mechanisms with diverse performance outcomes (Bargh & Ferguson, 2000; Croskerry, 2009a; Croskerry, 2003; Kahneman, 2011; Milkman, Chugh, & Bazerman, 2009; Monteiro & Norman, 2013; Norman et al., 2014; Redelmeier, 2005; Reyna, 2004; Shea & Frith, 2016). First, we replicated pupillometry findings from Kahneman et al. (1968) in that pupil size was larger for Type 2 thinking relative to Type 1 thinking. We also demonstrated that the engagement of cognitive control and the use of attentional resources are two main mechanisms that differentiate Type 1 and Type 2 thinking. Specifically, we found that Type 2 thinking required greater cognitive control and needed more attention focused towards the problem at hand. Our results demonstrate these mechanistic shifts as increases in frontal theta amplitude (Cavanagh & Frank, 2014; Cavanagh & Shackman, 2015) and decreases in parietal alpha amplitude (Klimesch, 2012; Sauseng et al., 2005), respectively. Our findings are congruent with existing literature that theorizes Type 2 thinking requires more cognitive resources to more thoroughly contemplate the task (Evans, 2011; Evans & Stanovich,

2013a, 2013b; Kahneman, 2011; Kahneman & Frederick, 2001; Kruglanski & Gigerenzer, 2011; Stanovich & West, 2000; Stanovich & Toplak, 2012; Varga & Hamburger, 2014). When engaging in Type 1 thinking, in contrast, cognitive control and attentional resources were required to a lesser extent (decreased frontal theta amplitude, increased parietal alpha amplitude) highlighting a reliance on automatic or routinized systems of the brain (Evans, 2011; Evans & Stanovich, 2013a, 2013b; Kahneman, 2011; Kahneman & Frederick, 2001; Kruglanski & Gigerenzer, 2011; Stanovich & West, 2000; Stanovich & Toplak, 2012; Varga & Hamburger, 2014). Further, we found that all measures were correlated. Kahneman and colleagues (1968) posited that pupil diameter was analogous to processing load – but it is unclear what this reflects. Here, we demonstrate that cognitive control and attention are two mechanisms that partly drive this effect. These correlations also imply that cognitive control (theta) and attentional mechanisms (alpha) are not independent and work in conjunction to result in Type 1 and Type 2 thinking.

With these findings, it may be tempting to summarize Type 1 and Type 2 modes of thinking as simply the absence or engagement of cognitive control and changes in the amount of attentional resources required. However, it is important to consider whether other mechanisms play a role. This consideration is supported by arguments for the value of network science (Börner, Sanyal, & Vespignani, 2007) in which investigation focuses on the functional relatedness of a set of mechanisms rather than focusing on mechanisms in isolation (Bressler, 1995; Bullmore & Sporns, 2009; McIntosh, 2000). For example, McIntosh (2000) posited that cognition arises from the activation and interaction of full-brain networks. Others have analyzed the findings of a mass of imaging studies on neural networks (across structural MRI, fMRI, diffusion tensor imaging, magnetoencephalography, and EEG techniques) and have further

specified that short-range neural connections adhere to highly specialized processes while long-range neural connections correspond to integrative processes (Bassett & Bullmore, 2006; Bullmore & Sporns, 2009; Sporns & Zwi, 2004) – classifications that seem parallel to Type 1 and Type 2 thinking. Our findings support this by demonstrating a concomitant relationship between frontal and parietal neural activity during different modes of thinking. Based on our findings and the aforementioned work, we believe that there remains merit in adopting Type 1 and Type 2 labels as long as we remain mindful that these terms encompass a range of interrelated cognitive mechanisms.

CHAPTER THREE: EXPERIMENT TWO – THE NEURAL BASIS OF CLINICAL REASONING: INVESTIGATION OF TYPE 1 AND TYPE 2 DECISIONS

3.1. Introduction

Everyday clinicians must sort and process an abundance of information diagnosing medical conditions. These decisions are imperative to the health of their patients. With severe time constraints, do clinicians resort to quick judgments or do they work extraneous hours ensuring that no detail is missed? Within the medical literature, there has been a push towards dual-process models to explain how clinicians make diagnostic decisions (Croskerry, 2009a; 2009b). Whereas fast, automatic, and effortless judgments have been labelled as Type 1 decision making, slow, contemplative, and effortful judgments have been classified as Type 2 decision making (Stanovich & West, 2000). Type 1 judgments are often thought to be quicker, but error-prone (Shae & Frith, 2016). Type 2 decisions, in contrast, require ample cognitive resources which could result in negative consequences such as fatigue (Holroyd, 2016). A recent review, however, has described how contemplative decisions may also be prone to errors (Norman, 2017), indicating that Type 1 decision making processes may be more efficient in some contexts. More specifically, Norman (2017) suggested that errors arise from cognitive biases with Type 1 reasoning, yet errors also surface with Type 2 decisions due to knowledge deficits. Although research to minimize Type 1 errors have only resulted in minor improvements, becoming an expert can largely moderate Type 2 errors (see Norman, 2017).

Above accruing a larger catalog of knowledge to diminish deficits, experts are more efficient in identifying and ignoring irrelevant information while focusing on relevant information (Ericsson, Prietula, & Cokely, 2007; Garcia-Retamero et al., 2009; Norman et al., 2014; Shanteau, 1992). For example, when teaching students to diagnose diseases, Williams and

colleagues (2017) found that medical training reduced the time needed to diagnose patient case studies. Moreover, there was a decreased involvement of the frontal cortex – a region involved in contemplative problem solving (see also Anderson, Hecker, Krigolson and Jamniczky, 2018). Specifically, they investigated neural signals of the frontal cortex via the reward positivity brain potential. The reward positivity arises 250 – 350 ms following performance feedback and is posited to reflect prediction errors – the discrepancy between a person’s expectation of an outcome and the actual outcome (Proudfit, 2015). Thus, as someone learns, their expectations more closely match the outcome and the reward positivity diminishes. In Williams and colleagues’ (2017) study, the reduced reward positivity indicated that students were able to effectively assess the medical cases and reach confident diagnoses. These findings, however, focused on how students learned to diagnose diseases and not specifically how they made these diagnostic decisions.

Hruska and colleagues (2016b), conversely, did compare decision making processes between expert and novice clinicians. They found that novices more heavily relied on the left prefrontal cortex while experts recruited the right prefrontal cortex. This suggested that novices relied on causal explanations and inference knowledge while experts’ cognition reflected a process that considered the correctness of their decisions in contrast to a normative standard. What is unclear, however, is which underlying cognitive mechanisms drive these differences. Recently, Williams, Kappen, Hassall, Wright, and Krigolson (in preparation) established that Type 2 decision making elicited increased recruitment of cognitive control and attentional mechanisms in comparison to Type 1 decisions. They had participants retain four digits in one condition (Type 1) and complete mathematical computations (Type 2) in another while measuring frontal theta and parietal alpha frequency bands. Whereas increased frontal theta (4 –

8 Hz) has been linked to increased cognitive control (Cavanagh & Frank, 2014), decreased parietal alpha (8 – 12 Hz) has been theorized to reflect increased attention (Klimesch, 2012). Findings demonstrated that Type 2 decision making processes elicited increased frontal theta and decreased parietal alpha power than Type 1 decision making processes (Williams et al., in preparation). Although this study assessed Type 1 and Type 2 decision making when completing a task unlike making diagnostic decisions, theorists have argued that these processes occur similarly across contexts (Evans & Stanovich, 2013a). None-the-less, it is unclear whether these findings are generalizable to medical contexts.

In the present study, we replicated the electroencephalography (EEG) variant of the Cards paradigm (Williams et al., 2017) and extended it to assess Type 1 and Type 2 decision making processes. We hypothesized that accuracy rates would increase, patient card view times would decrease, and the reward positivity would diminish from the beginning of training (untrained students) to the end of training (trained students). Further, we expanded this paradigm by having participants assess one-hundred and twenty additional medical cases after they had completed training. We hypothesized that frontal theta would decrease, and parietal alpha would increase, from early to late in training and remain at these levels while completing the additional cases.

3.2. Methods

3.2.1. Participants

Thirty-three undergraduate students from the University of Victoria's Psychology department were recruited through the use of an online sign-up system. Of these participants, 22 ($M_{\text{age}} = 23$ [95% CI: 21, 25], 13 females) completed the task and learned to diagnose diseases to high levels of accuracy. As we were here interested in determining the effects of becoming an

expert on Type 1 and Type 2 decision making, we only analyzed the participants that learned. All participants had normal or corrected-to-normal vision, no neurological impairments, and received extra course credit in a psychology course. All participants provided informed consent approved by the Human Research Ethics Board at the University of Victoria (protocol number: 16-428), and the study followed ethical standards as prescribed in the 1964 Declaration of Helsinki and subsequent revisions.

3.2.2. Apparatus and Procedures

In a sounds dampened room, participants were seated in front of a 19" LCD monitor and used a 5-button RESPONSEPixx (VPixx, Vision Science Solutions, Quebec, Canada) to respond in accordance to the task. The task was similar to that of Williams et al. (2017) which was adapted from the Cards paradigm (Bannister et al., 2016; Burak, McLaughlin, Coderre, Busche, & Raman, 2015; Horrey, Keegan, Paget, & Tan, 2016; Kazoleas, 2016; Tang et al., 2016). The task was coded in MATLAB (Version 8.6, Mathworks, Natick, U.S.A.) using the Psychophysics Toolbox extension (Brainard, 1997) and is available at <http://www.krigolsonlab.com/source-code.html>.

Participants were presented fictional 'patient cards' that contained 10 physiological readings and an image of their 'patient' (see Figure 1). Each card included five variables that were necessary for diagnosing diseases (alkaline phosphatase, alanine aminotransferase, aspartate aminotransferase, gamma-glutamyl transferase, ultrasound reading) and five variables that were distractors (heart rate, blood oxygen level, blood pressure, respiratory rate, temperature) which corresponded to a liver (mild hepatocellular, moderate hepatocellular, severe hepatocellular) or biliary (cholestatic intrahepatic, cholestatic extrahepatic) disease (see Table 1). Variable accuracy and validity was confirmed by a medical doctor within the Department of

Medicine at the University of Calgary (Williams et al., 2017). The variables were presented in green, purple, blue, yellow, and white Arial font from top to bottom and a patient image was randomly determined, without replacement, from a pool of 357 profiles (69% female; Minear & Park, 2004). Patient images were reused once they had all been presented.

On each trial, participants were able to view the patient cards as long as they needed and were to press a button to present the diagnostic options to make a diagnosis (see Figure 1). The diseases were displayed on the top, bottom, left, and right of the screen and had a coloured border (top: yellow, bottom: blue, left: green, right: red) to match both the orientation and the button colours of the response box used. The disease name locations were randomly determined. A selected response would illuminate and could either be confirmed by selecting the white button or cancelled by selecting any of the other buttons. A white fixation cross was then presented for 400 – 600 ms followed by feedback that corresponded to the accuracy - correct ('✓') or incorrect ('X') – of the response (see Figure 1). This was followed by another white fixation cross for 400 – 600 ms to complete the trial.

The experiment was conducted over six phases: the first five of which involved learning, and the last involved making learned decisions. In the first four learning phases, participants were to learn to diagnose diseases in a step-wise function. In the first phase, they only needed to distinguish between two randomly selected diseases. Correspondingly, participants were only presented two diagnostic options. To proceed to the next phase, participants had to achieve a 90% or higher accuracy rate for two consecutive blocks, each containing 20 patient cards. When attained, a new disease was randomly introduced to the previously learned diseases. In phase five, participants continued to learn just as phase four, with all five diseases, to ensure that participants received a large number of exposures to all diseases and progressed by achieving

90% or higher on two consecutive blocks. In phase six, participants entered the learned decision phase, where they were presented 24 case-studies of each disease across six blocks. They did not, however, receive feedback as to their accuracy. As a note, this is in contrast to how this is taught traditionally in medical education where students receive the diagnostic information ahead of time, memorize this information, and then apply it to medical cases.

Table 1. *Physiological ranges for all diseases. ALP = alkaline phosphatase, ALT = alanine aminotransferase, AST = aspartate aminotransferase, GGT = gamma-glutamyl transferase. The other distractor data was held constant across diseases: heart rate: 65 - 85, blood oxygen level: 98, blood pressure: 120-140/70-80, respiratory rate: 12-20, temperature: 35.5-37.*

Disease	ALP	ALT	AST	GGT	Ultrasound
Cholestatic Intrahepatic	200 – 300	10 - 40	8 – 32	100 -200	Not abnormal
Cholestatic Extrahepatic	10 - 50	8 - 40	300 - 600	200 – 400	Dilated bile ducts
Mild Hepatocellular	30 – 145	80 – 150	40 – 200	200 – 400	Not abnormal
Moderate Hepatocellular	30 – 145	300 – 600	275 – 300	200 – 400	Not abnormal
Severe Hepatocellular	30 – 145	850 - 1100	600 – 800	85 – 150	Not abnormal

After the experiment, participants were given two pen-and-paper post-tests that each consisted of 20 novel case-studies and the five diseases in multiple choice format. One of these post-tests was presented upon completion of the task, while the other was completed 24 hours later. The presentation of the two post-tests were counterbalanced.

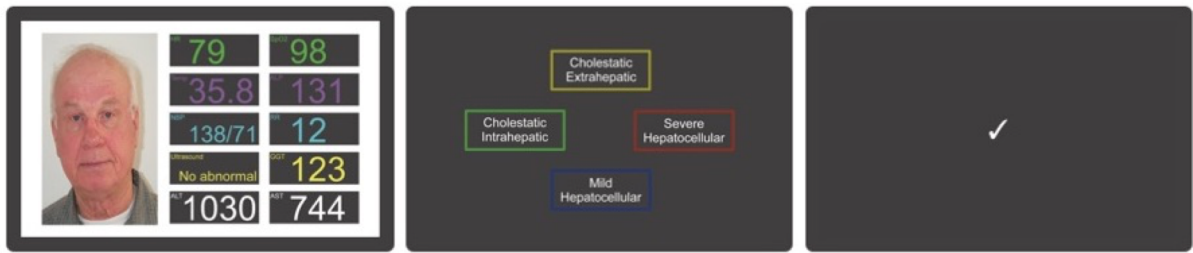


Figure 1. Patient card containing ten physiological readings and an image of the patient (left), diagnostic options (middle), and feedback stimuli (right).

3.2.3. Data Acquisition and Processing

Behavioural data of interest included accuracy rates and the time participants viewed the patient card. These data were categorized as the first twenty trials of phase one (early) and the last twenty trials of phase five (late). Electroencephalographic (EEG) data was recorded at a sampling rate of 500 Hz using Brain Vision Recorder software (Version 1.10, Brain Products GmbH, Munich, Germany) via an ActiCHamp (Revision 2, Brain Products GmbH, Munich, Germany) with an 8 kHz antialiasing low-pass filter and measured 64 electrodes within a standard ActiCAP layout (Brain Products GmbH, Munich, Germany). Electrodes were referenced to a common ground and impedances were on average kept below 20 k Ω . Temporal accuracy was guaranteed using a DATAPixx processing box (VPixx, Vision Science Solutions, Quebec, Canada).

Post experiment processing of the EEG data was conducted in Brain Vision Analyzer (Version 7.6, Brain Products GmbH, Munich, Germany) and MATLAB (Version 8.6, Mathworks, Natick, U.S.A.). First, excessively noisy and faulty electrodes were removed, data was down sampled to 250 Hz, and re-referenced to an average mastoid reference (electrodes TP9 and TP10). Next, alongside a notch filter of 60 Hz, a dual-pass Butterworth filter was applied

using a high-pass of 0.1 Hz and a low-pass of 30 Hz. Data was then epoched to 1000 ms prior to the events of interest to 2000 ms following the event to facilitate independent component analysis (ICA). ICA was conducted with restricted infomax and classic PCA sphering parameters. Components reflecting ocular activity were manually selected and removed dependent on the factor loadings and headmaps. Data was then reconstructed using the remaining components. Electrodes that were removed early within processing were then interpolated using the method of spherical splines and data were baseline corrected using a pre-stimulus epoch from -200 to 0 ms.

First, we assessed the reward positivity – a neural correlate of prediction errors (Proudfit, 2015). For this, data were re-segmented from -200 ms to 600 ms corresponding to the correct feedback stimuli, and put through artifact rejection with 200 μ V absolute difference and 20 μ V/ms gradient criteria (14% [10%, 18%] of segments rejected). Data was separated into the correct trials within the first twenty trials of phase one (early) and the last twenty trials of phase five (late). The conditional waveforms were averaged for each participant and difference waveforms were created by subtracting early from late conditions. Conditional and difference waveforms were grand averaged across participants. The mean peak of the reward waveforms was determined by first finding the maximum peak of each participants' difference waveform within the time range of 250 ms to 400 ms at channel FCz (see Proudfit, 2015), and then averaging the data \pm 25 ms surrounding the average of these peaks (304 ms). These processes were conducted in congruence with Williams and colleagues (2017).

For the theta and alpha analyses, data was then exported to MATLAB in an EEGLAB format (Delorme & Makeig, 2004). Within MATLAB, data was segmented from 0 ms to 2000 ms focused on the presentation of the patient card. Artifacts were rejected if epochs exceeded a

200 μV maximum-minimum difference or a 20 $\mu\text{V}/\text{ms}$ gradient (18% [14%, 23%] of segments rejected). The data was separated as early, late, and post. Early was categorized as the first forty trials of phase one and late was categorized as the last forty trials of phase five. Moreover, post was classified as the last forty trials of the learned decision phase (i.e., phase six). We then conducted a Fast Fourier Transform (FFT) without tapering and averaged the FFTs for each condition and participant. Informed by Williams and colleagues (in preparation), theta activity was classified as 4 – 6 Hz at channel Fz and alpha was measured as 11 – 12 Hz at channel CPz. Although it may be restricting to broadly group frequency bands into cognitive mechanism analogs, it is important to note that it is standard to measure ‘theta’ as the frequency range of 4 – 7.5 Hz and ‘alpha’ as the 8 – 13 Hz range (de Silva, 2013). Here, we decided on reduced bands due to consistencies across frequency ranges determined via visualization of the data. Although we will continue to use the terms theta and alpha, we caution that these may be better described as low-theta and high-alpha, respectively.

3.2.4. Data Analysis

To determine effects of learning and expertise, post-test scores, the accuracy of decisions, time viewing the patient card, and reward positivity amplitude were compared across early and late conditions. First, we conducted a one-sample t-test comparing the first post-test to chance (20%). We also conducted a paired samples t-test comparing the first and second post-test. As four of the 22 participants did not complete one of the post-tests, only 18 participants were included in these analyses. Further, we conducted a series of paired samples t-tests for accuracy rates, card view times, and reward positivity amplitude comparing early and late conditions. To compare effects of cognitive control and attention across expertise, theta and alpha were compared between early, late, and post conditions using a one-way paired samples ANOVA for

each measure. We set alpha to 0.05 for all inferential tests and all t-tests were two-tailed. For all reported mean values, we also report 95% confidence intervals.

3.3. Results

To determine whether the participants became experts in diagnosing diseases, we assessed post-test scores, accuracy rates, reaction times, and the reward positivity amplitude. The first post-test resulted in an average score of 98% [96%, 100%], which was reliably higher than chance (20%), $t(17) = 94.92, p < .0001, d = 22.37$. Furthermore, the second post-test (99% [98%, 100%]) 24 hours later did not differ from the first, $M_d = 1\% [-1\%, 3\%], t(17) = 0.90, p = .3808, d = 0.21$. The accuracy rates of participants increased from early ($M = 74\% [66\%, 82\%]$) to late ($M = 98\% [96\%, 99\%]$) in learning, $M_d = 23\% [16\%, 31\%], t(21) = 6.52, p < .0001, d = 1.39$ (see Figure 2). Note that early accuracy rates were above chance (50% in phase one as they were diagnosing two diseases) and this was reflective of the fact that some participants had already begun to learn within these first twenty trials. Reaction times correspondingly decreased from early ($M = 12.57 \text{ s} [9.81 \text{ s}, 15.33 \text{ s}]$) to late ($M = 5.39 \text{ s} [4.70 \text{ s}, 6.07 \text{ s}]$) in learning, $M_d = -7.18 \text{ s} [-9.65 \text{ s}, -4.72 \text{ s}], t(21) = -6.06, p < .0001, d = -1.29$ (see Figure 2). In addition, the amplitude of the reward positivity decreased in amplitude from early ($M = 4.90 \mu\text{V} [2.95 \mu\text{V}, 6.85 \mu\text{V}]$) to late ($M = 1.44 \mu\text{V} [0.14 \mu\text{V}, 2.74 \mu\text{V}]$) in learning, $M_d = -3.46 \mu\text{V} [-5.63 \mu\text{V}, -1.28 \mu\text{V}], t(21) = -3.31, p = .0033, d = -0.71$ (see Figure 3).

Next, we examined the power in the theta (4 – 6 Hz) and alpha (11 – 12 Hz) bands in order to examine the effects of learning on Type 1 and Type 2 decisions (see Figure 4). There was no effect of expertise on frontal theta, $F(2,42) = 0.19, p = .8249, \eta_g^2 = 0.003$ (assumption of sphericity met, $X^2(2) = 3.85, p = .1458$), or parietal alpha, $F(2,42) = 0.46, p = .6012, \eta_g^2 = 0.003$ (with a Greenhouse-Geisser correction as assumption of sphericity was not met, $X^2(2) = 6.00, p =$

.0499).

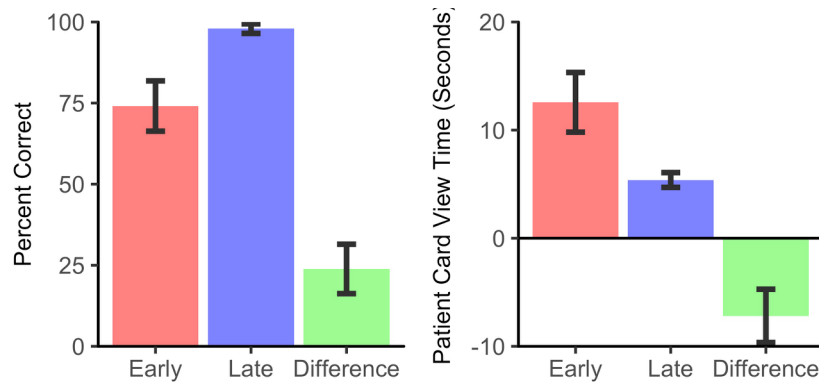


Figure 2. Behavioural results of accuracy rates (left) and patient view time (right) for early, late and the difference (late – early). Early represents the first twenty trials of training while late is the last twenty trials of training. Error bars represent 95% confidence intervals.

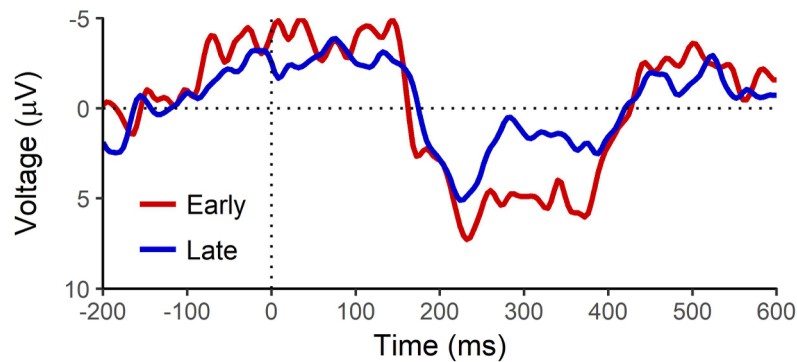


Figure 3. The correct waveforms of the reward positivity at channel FCz for the early and late conditions time locked to feedback stimulus onset. Early represents correct trials within the first twenty trials of training and late represents the correct trials within the last twenty trials of training.

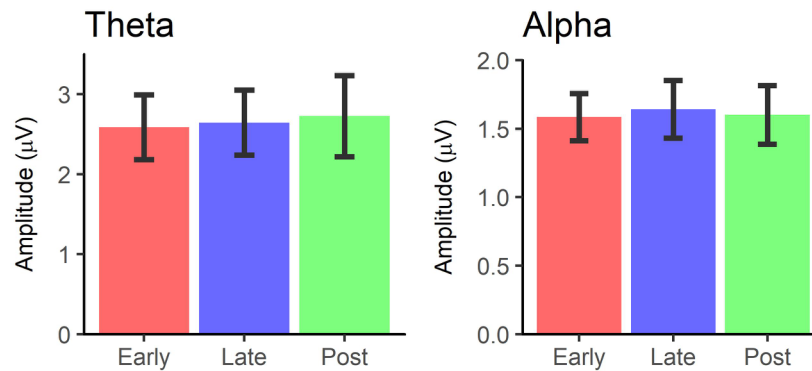


Figure 4. Theta activity at channel Fz (left) and alpha activity at channel CPz (right) time-locked to the onset of the patient cards for the early, late, and post conditions. Early refers to the first forty trials of training, late refers to the last forty trials of training, and post is the last forty trials of the learned decision phase. Error bars represent 95% confidence intervals.

3.4. Discussion

Experts clinicians are thought to rely on Type 1 decision making processes resulting in quicker and more accurate decisions (Ericsson, Prietula, & Cokely, 2007; Eva & Regehr, 2007; Evans, 2008; Garcia-Retamero et al., 2009; Monteiro & Norman, 2013; Norman, 2017; Norman et al., 2014; Reyna, 2004; Shanteau, 1992). Here, we replicated findings from Williams and colleagues (2017) that students learned to diagnose diseases to a high levels of accuracy as indicated by high post-test scores (98% accuracy). We extended these findings by demonstrating the persistence of this knowledge for 24 hours on a second post-test (99% accuracy). Moreover, we replicated findings (Williams et al., 2017) that accuracy rates increased and patient card view times decreased when participants were trained in comparison to when they were untrained. Neural indicators of learning - i.e., the reward positivity – also diminished across training. These findings together may indicate that the students learned to levels of expertise. In contrast to our hypotheses, however, there were no differences between frontal theta and parietal alpha as a function of expertise. These findings may imply that Type 1 decision making processes are not,

in fact, recruited in expert clinical reasoning. There are, however, alternative reasons that may too explain our results.

Diagnosing diseases is not a simple task (Crosskerry, 2009a; 2009b). Although clinicians undergo many years of education and many more of practice, it is important to consider whether these decisions are able to become so routinized that Type 1 decision making processes are adequate to reach accurate judgments. In the medical literature it is, in fact, believed that this could occur (Croskerry, 2009a). Croskerry (2009a) posited that if a clinician recognizes salient features of a disease, they will rely on Type 1 pattern recognition mechanisms. Further, he described that this could only occur through a vast exposure of similar cases which formerly needed to recruit Type 2 decision processes (i.e., expertise). If this is so, then why was it that our results did not align with those of Williams and colleagues (in preparation)? This may be explained by claims put forth by Evans and Stanovich (2013a) and Kahneman (2011). Specifically, these researchers posit that Type 1 and Type 2 decision making is not dependent upon two single neural networks, but is instead comprised of multiple networks. Thus, making a Type 1 or Type 2 decision in one context may not necessarily recruit the same cognitive mechanisms as doing so in another context. Williams et al. (in preparation) had participants remember a string of numbers in one condition and complete mathematical computations in another condition. This is instead comprised of Type 1 decision making that involved the retention of numbers and Type 2 decision making that required mathematical computations. Here, we had participants diagnose diseases through pattern recognition mechanisms (Williams et al., 2017). Thus, if both our paradigm and that of Williams et al. (in preparation) recruited Type 1 and Type 2 decision making processes, it is possible that these required different cognitive capabilities. For example, in Williams et al. (in preparation) these processes may more

heavily rely on working memory mechanisms, while in our experiment the reliance falls within pattern recognition and categorization mechanisms. Specifically, within clinical reasoning it is necessary to explore and contrast patient physiological data in order to assess the health of said patient. Further, this analysis leads to the categorization of symptoms into possible diseases. Thus the findings of one experiment may not be generalizable to the other. It will then be necessary for future research to take into consideration differences in task demands.

An alternative explanation, however, could be that our trained students were not, in fact, experts. In 1967, Fitts and Posner proposed three stages of learning: cognitive, associative, and autonomous. Within the cognitive stage, broad task goals and decision standards are realized. Within the associative stage, individuals focus and fine-tune particularly difficult aspects of the decision standards they have placed. Finally, the autonomous stage involves the repeated practice of a task until routinization and automatization is achieved. It is unclear, and doubtful, that our participants were able to achieve this final stage in the short period of time in which they had to complete the task. Ericsson and colleagues (2007) indicated that becoming an expert takes decades, and Ericsson, Krampe, and Tesch-Römer (1993) described this process to take 10,000 hours, or ten years. In our task, students trained for about one hour, thus not coming anywhere near these standards. The claims of Ericsson and colleagues (1993; 2007), however, are to become an expert in an entire field of study, while we only had students become experts in a small category of diseases. Thus, these time commitments may not here apply. As an alternative to measuring expertise, Ericsson and colleagues (2007) specified that an expert has the following qualities: their performance is equivalent to other experts, their decisions consistently lead to successful results, and their performance can be measured and replicated in the lab. Our findings adequately support the latter two of these criteria – after training, participants yielded an average

accuracy rate of 98% which was maintained and replicated on a post-test the following day. As of yet, however, we have not tested whether their results are comparable to expert clinicians – certainly the next step to ensuring our trained students are true experts. Thus, we do not have enough evidence to conclude that our participants were, in fact, experts. Moreover, it is not clear whether accuracy rates by themselves are precise enough to reflect a shift of processes from Type 2 to Type 1. Future research could be longitudinal, tracking medical students throughout medical education and residency. This would ensure that we are truly tracking changes brought about by experience.

In summary, we were able to train students how to diagnose diseases. We had theorized that this would result in expertise judgments and heavier reliance on Type 1 decision making processes. Our findings did not confirm this. Specifically, trained participants did not elicit a decrease in cognitive control – as indicated by a decrease in frontal theta – and in attention – as reflected by an increase in parietal alpha - as would be congruent with Williams et al. (in preparation). In contrast to concluding that expert clinical reasoning does not recruit Type 1 decision making processes, we pose that this may be because this task recruited different Type 1 and Type 2 decision making networks than Williams et al. (in preparation), and that our students may not have been practiced enough to truly be considered experts.

CHAPTER FOUR: CONSIDERATIONS AND DISCUSSION

4.1. Implications

It is necessary to understand how we make decisions so that we can predict when we will make mistakes and how to optimize our problem solving. Some of my findings indicate that cognitive control and attentional mechanisms underlie Type 1 and Type 2 decision making processes under selected contexts. Specifically, in my first experiment increased cognitive control (increased frontal theta) and attention (decreased parietal alpha) were indicators of Type 2 decision making. Although this was not replicated in my second experiment, there may be several explanations as to why. It could be that the task used was too complex or that our participants were not yet experts. Alternatively, the discrepancy between experiments could instead point to the complexity that underlies Type 1 and Type 2 decision making in that the mechanisms involved may vary across contexts.

The two presented experiments were quite different. Whereas the first experiment required working memory and mathematical skills, the second relied on pattern recognition and stimulus-response mappings. Although Evans and Stanovich (2013a) have advocated that these Type 1 and Type 2 decision making processes are domain general in that they should appear across contexts, they are unclear as to which contexts they would arise. Further, they claim that each process is built of multiple systems in themselves thus what constituted Type 1 (or Type 2) processing in one context may not generalize to another. Thus, the experiments here described may each be recruiting Type 1 and Type 2 processes, yet the discrepant task demands may rely on different systems. Although I set out to evaluate common mechanisms of Type 1 and Type 2 decision making processes across contexts, perhaps I was only able to determine one instance of the multitude of existing systems. Thus, the exploration into these processes must continue the

search for other systems. None-the-less, it is necessary to recognize the influence of cognitive control and attention in these types of processes as it opens way for theoretical and applicable implications.

4.1.1. Theory

What exactly is cognitive control? Cavanagh and Frank (2014) describe cognitive control to be a top-down influence on habitual responses which adapts behaviour (see also Cavanagh & Shackman, 2015). Specifically, they describe that this (and theta) first reflects a realization for the need of control contingent on endogenous motor activity or exogenous percepts. In my recent review (Williams, Hecker, Wright, & Krigolson, in preparation), I posited that this may be a process wherein external demands (e.g., task difficulty) are integrated with internal capabilities (e.g., attentional resources and motivation). Second, Cavanagh and Frank (2014) describe an instantiation of action wherein this signal is communicated to other regions of the brain. What is unknown, however, is whether this transmission includes information or is simply an alarm signal for the need of control.

In any case, Cavanagh and Frank (2014) summarize frontal theta to reflect a signal of surprise brought about by uncertainty. If uncertainty is the main drive of recruiting cognitive control mechanisms, it is no surprise that my two experiments do not align. When completing the add-one task in experiment one, the trials were randomized so that participants could not be sure whether they were about to encounter an easy or difficult condition. Conversely, there is no ambiguity in the medical cards task in experiment two - participants were well aware as to the difficulty of each upcoming case. Additionally, it has been theorized that this signal only arises when there is a need to override habitual responses (Cavanagh & Frank, 2014; Cavanagh & Shackman, 2015). This further explains results in experiment one in that for Type 2 decisions

there was a need to override prepared responses (i.e., the presented digits) but for Type 1 decisions there was not. In summary, cognitive control computes and communicates the degree of necessary resources to override a prepared response when under uncertainty.

Correspondingly, attention is a complex phenomenon and it is important to clarify how it is involved in Type 1 and Type 2 decision making. First, it has been theorized that a decrease in alpha amplitude results in an enhanced focus on task-relevant information (Bauer, 2012; de Silva, 2013; Klimesch, 2012). Type 2 decision making requires a larger set of task-relevant information compared to Type 1 decision making - leading to a decreased alpha. Second, Klimesch (2012) has posited that attention in fact involves memory mechanisms. Specifically, he suggested that a decrease in alpha activity is analogous to the access and retrieval of information from a knowledge storage system (e.g., declarative memory). This can explain the discrepancy of findings across my two experiments. In experiment one, Type 2 decisions involved the retrieval of information (e.g., mathematical rules and new solutions) while Type 1 judgments did not. Moreover, in experiment two, participants would need to retrieve the same information (e.g., disease-based rules) regardless of level of expertise. In other words, experts were more efficient at using the *same* information as novices. In summary, Type 2 decision making processes involve increased attentional capacities to investigate the environment and retrieve additional knowledge.

Further findings from experiment one demonstrated that cognitive control and attention are interrelated. In my review, I proposed ‘process selection’ and ‘process execution’ steps to decision making. Whereas process selection involves a computation that signals the degree to which additional cognitive resources are needed, process execution reflects the additional processes required to reach a decision. These definitions seem analogous to cognitive control and

attention in that process selection may reflect cognitive control computations and communications while process execution involves attentional and memory mechanisms. Specifically, when encountered with a problem, frontal cognitive control mechanisms compute whether this could be solved reflexively or whether additional contemplation is needed (Cavanagh & Frank, 2014; Cavanagh & Shackman, 2015). A signal with this computation is then projected to parietal attentional mechanisms which retrieve additional knowledge dependent on the magnitude of the signal. An important consideration here would be that dual-process theories (e.g., Evans & Stanovich, 2013a) would claim that this signal must surpass a threshold to recruit these attentional mechanisms while continuous theories (e.g., Kruglanski & Gigerenzer, 2011) would posit that different degrees of attention would be recruited in proportion to the transmitted signal. Additionally, these attention-memory mechanisms likely interact with working memory (Evans & Stanovich, 2013a) and rule-following mechanisms (Kruglanski & Gigerenzer, 2011) to reach a decision.

4.1.2. Application

One implication to discovering the involvement of cognitive control and attentional mechanisms in Type 1 and Type 2 decision making processes would be to use the corresponding measures – frontal theta and parietal alpha – to assess how people are making decisions in the real-world. Having these measures of decision making processes can be utilized in many professional environments including within the hospital. With the growing use of portable EEG systems (e.g., Krigolson, Williams, Norton, Hassall, & Colino, 2017), these measurements can be used in contexts that are out of the bounds of standard EEG system capabilities. In regards to medical settings, future research can determine whether medical students and professionals are making quick Type 1 decisions or contemplative Type 2 decisions while diagnosing patients.

There are advantages to each of these processes. Whereas some theorists hypothesize that generally Type 1 decision making processes can save time leading to more cases diagnosed (Bargh & Ferguson, 2000; Dijksterhuis & Nordgren, 2006; Milkman, Chugh, & Bazerman, 2009; Reyna, 2004; Shae & Frith, 2016), others posit that Type 2 judgments may be more accurate (Croskerry, 2003; Croskerry, 2009a; Kahneman, 2011; Norman et al., 2014; Monteiro & Norman, 2013; Redelmeier, 2005). In a setting such as the hospital, errors are costly, but so is the time of medical professionals (Milkman et al., 2009). It is then important to find a balance between time and accuracy so that efficiency is accompanied with correct decisions. The application then moves beyond simply measuring how these students and professionals are making decisions but also how they may optimize their judgments through training informed by these measures.

Biofeedback training utilizing neural measures of decision making processes could aid students and professionals achieve a perfect balance of accuracy while not taking too long to reach a decision. Although reflective processing has been shown to increase accuracy when diagnosing difficult case studies, performance decreased for easy cases (Mamede et al., 2010). This is in congruence with research exploring the effects of expertise on these processes (Eva & Regehr, 2007; Eva, Link, Lutfey, & McKinlay, 2010; Lieberman et al., 2004; Monteiro & Norman, 2014). Additionally, other effects of individual differences have been shown to impact Type 1 and Type 2 decision making including general cognitive ability (Evans, 2003; Stanovich & West, 2000), intelligence (Evans, 2006; Evans & Stanovich, 2013a; Kyllonen & Dennis, 1996; Kyllonen & Christal, 1990; Stanovich, 1999; Stanovich & West, 2000), and age (Evans, 2003; Gilinsky & Judd, 1994). Biofeedback training would then necessarily have to incorporate individual differences which can be collected with baseline tests.

Of course, these applications are not limited to the medical field. Biofeedback training suggests that we could learn to control our brain states. If this is possible then we could learn to put ourselves in a state of ‘flow’ (Csikszentmihalyi, 1990) – a brain state of immense concentration leading to easy and optimal functioning. Of course, this ability will be beneficial across all environments. For example, being able to train students to achieve flow states could lead to better learning, understanding, and testing. Moreover, ensuring athletes are in a state of flow could guarantee that they make that game-winning shot, catch, or kick. Finally, (because I am a science fiction enthusiast) having the first colonists of Mars in a state of flow will ensure that they are well prepared to solve any unexpected emergency.

4.2. Limitations and Future Directions

This proposed research is limited in several ways. In my review, I described that the models (e.g., Evans and Stanovich, 2013a; Kahneman, 2011) in which this research is based upon are untestable (Keren, 2013; Keren & Schul, 2009). These models have also put forth broad claims of mechanisms that may drive these different decision making processes (e.g., working memory; Evans & Stanovich, 2013a). The mechanisms themselves are not what many critics argue against, however, it is the ambiguity of what they encapsulate that is criticized (Keren, 2013). My findings fall into similar ambiguity. What we know about the aspects of cognitive control and attention that theta and alpha truly reflect are limited (Cavanagh & Frank, 2014; Klimesch, 2012). To further this research, we must continue to investigate these neural frequencies and determine specifically what they represent.

Another limitation is the generalizability of these results. Here, the goal was to determine parallel underlying mechanisms across two very different tasks. Unfortunately, this goal was not met – demonstrating the involvement of cognitive control and attention in one task but not the

other – and this points to the difficulty that this field of research has had (and will continue to have) to generalize results into a single theory. Moreover, the presented studies were independent with different participants, thus the comparison between them can only be speculative. Further research would benefit by having the same participants complete these and other tasks that have been used as evidence for Type 1 and Type 2 decision making (e.g., Cognitive Reflection Test; Frederick, 2005).

A third limitation is the analysis used – namely Fast Fourier Transforms (FFT). Although FFT analyses reliably measure the recruitment of different frequencies, it is temporally imprecise. For example, in experiment one I averaged data over a second of time and in experiment two I did so over two seconds. A time-frequency analysis, in contrast, could deliver frequency information without losing temporal accuracy. I opted not to use this technique, however, because I predicted that Type 1 and Type 2 decision making processes can vary immensely between and within individuals. For example, some people may take more time to recruit Type 2 decision making processes than others, but also the same person may take more time to do so on one trial compared to another. FFT measurement techniques are not sensitive to these variations, however, time-frequency analyses are. Thus, further research may want to utilize this latter technique but must do so with caution – at least until variations can be accounted for.

In regards to the applicability of this research, it was not here explored as to whether theta and alpha are measurable using portable EEG devices (which real-world applications are dependent on). Krigolson and colleagues (2017) demonstrated the Muse headband as an effective tool for extracting event-related-potential components, but not frequency components. Extracting frequency data, however, is reliant on acceptable EEG quality (Luck, 2014), which they have

demonstrated. Thus, it is likely that this device would be effective when collecting frequency data during Type 1 and Type 2 decision making. Krigolson et al. (2017), however, do list multiple limitations to this device. Among these include noisier data and limited electrode locations in comparison to standard systems. As FFTs are less prone to noise (Luck, 2014), this is an advantage to using frequency analyses. Moreover, even though this device does not have electrodes Fz and CPz as would be optimal to measure frontal theta and parietal alpha (as presented in experiment one), the available electrodes (e.g., Fpz and a combined TP9/TP10, respectively) may be adequate in capturing this activity. Of course, future research will have to explore these claims to ensure an effective assessment strategy for Type 1 and Type 2 decision making processes in the real-world. Finally, it will also be necessary to ensure that one can, in fact, voluntarily modulate these brain frequencies in order for biofeedback training and brain state manipulation (e.g., state of flow) to be successful.

4.3. Conclusions

Understanding how humans make decisions is necessary for both theoretical and applied sciences. Here, I presented an extensive review of Type 1 and Type 2 decision making and two EEG experiments that attempt to decipher the underlying mechanisms that drive these processes. In my review, I highlighted how theorists argue whether these processes are discrete (dual-process) or two extremes of the same process (continuous). Although each of these approaches have been modelled, critics question their validity. In my first experiment, the recruitment of Type 1 and Type 2 decision making processes was manipulated by having participants retain numbers and complete mathematical computations, respectively. I demonstrated that Type 2 decision making processes recruited more frontal theta and less parietal alpha in comparison to Type 1 decisions, indicating the involvement of cognitive control and attentional mechanisms. In

experiment two, I manipulated Type 1 and Type 2 decision making processes as a factor of expertise in a medical context. I did not see any differences in theta or alpha, concluding that medical experts may not rely on Type 1 decision processes. Alternatively, I proposed that these findings may be due to the varying cognitive mechanisms that may underlie Type 1 and Type 2 decision making, or that our participants were not true experts.

In summary, Type 1 and Type 2 decision making processes are complex and vary across contexts. Although multiple models exist to explain how humans make decisions, there is still a need for more development. Mechanisms of cognitive control and attention are likely involved in Type 1 and Type 2 decision making, however, this may not be true in all contexts. It is then important to explore these decision making processes while considering a variety of environments and demands.

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