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Master thesis

Preparing for the crises of tomorrow: The role of balance between cognitive styles

A quantitative study of the explanatory power of balance between cognitive styles on task performance in a simulated crisis management setting

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Abstract

In this thesis we sought to explore the extent to which balance between cognitive styles explains variation in task performance in a simulated crisis management setting. We conducted a quantitative study with a sample consisting of 107 participants. Our findings revealed that individuals scoring medium-medium on intuitive and analytic style did not perform as well as the other balanced combinations, high-high and low-low. However, as our simple slope analysis contained two insignificant slopes, no firm conclusions could be drawn. Moreover, a directional difference score was created as a quantification of balance between cognitive styles, and its relationship with task performance was a negative quadratic regression equation with a maximum value at approximately d=0. This supports the predictive validity of balance between cognitive styles on task performance, and further suggests the most advantageous balance to be a near perfect balance between intuitive and analytic cognitive style. Lastly, the squared directional difference score was a significant predictor of task performance, and in addition to control variables, found to explain 35% of the variance in task performance. The model containing the interaction term, rather than the squared directional difference score, did, however, explain 2% more of the variance. Furthermore, balance between cognitive styles seem to explain almost all of the variance explained by the interaction term, with 4% and 5% respectively. These results have practical implications on recruitment and selection practices in crisis management settings, in addition to potential theoretical implications regarding the medium-medium combination, and whether the quantification of balance aligns with a dual-process perspective. As such, our findings indicate that taking a step forward requires us to take two steps back to reassess the basics of balance between cognitive styles.

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1. Introduction

Effective crisis management is crucial in overcoming the myriad of emerging crises. When shots began firing at Utøya, the response of the Norwegian police was slow and ridden with errors, resulting in potentially avoidable deaths (NOU, 2012:14, p. 450-454). In contrast, unarmed civilians Mohammed Iqbal Javed and Muhammad Rafiq stopped a shooter entering the Al-Noor Mosque, by quick and efficient response to the imminent threat. As a result, they prevented what could have turned into an even larger tragedy (Ansari, 2020; Brenna et al, n.d.). These examples emphasize how different responses to crises can drastically change the outcome. More importantly, it raises the question: Do we know what it takes to efficiently handle the crises of tomorrow?

Sound judgment and superior decision-making are considered the cornerstone for effective crisis management, particularly in pivotal, split-second decisions (Hidayat et al., 2009, p. 37). While there has been an immense effort to understand how situational and decisional characteristics can influence decision-making, less is known about the impact of individual differences (Mohammed & Schwall, 2009, p. 250). A full understanding of the mechanisms behind decision-making is further impaired by an overemphasis on main effects, and subsequently, inattention to interaction effects (Appelt et al., 2011). The lack of studies on individual differences and interaction effects exposes a research gap, a gap that paradoxically contradicts what the theoretical literature has suggested thus far.

For a long time, scholars have suggested that there exist individual differences in cognitive style, or the preference to think intuitively and analytically (e.g., Langley, 1995; Epstein, 1973; Pretz, 2008). From a dual-process perspective, intuition and analysis are further assumed to interact. Theorists have built on this by suggesting frameworks of interactive combinations, where one can score a high or low preference on both intuition and analysis, resulting in four different combinations of cognitive style (Epstein, 1998, p. 233; Hodgkinson & Clarke, 2007). Predictions have been made regarding the effectiveness of these combinations in different situations; however, few studies have been conducted to empirically test said predictions (Bakken et al., n.d.). Nonetheless, along with an increased concern and focus on crises, there is an equally growing need to address the psychological mechanisms behind the decision-making skills essential for successful crisis management (Bakken, 2013).

One of the few studies which have accounted for both individual differences and interaction effect, specifically in a crisis management setting, is one conducted by Bakken et al. (n.d.). They examined how the interaction between intuitive and analytic cognitive styles influence task performance in a volatile, uncertain, complex, and ambiguous (VUCA) environment under time restriction. They found that those with a balanced cognitive style, or an equal preference for both intuition and analysis, performed better than those with a clear preference for one style. Bakken et al. (n.d.) further suggested the main mechanism to be increased cognitive flexibility, which can be of particular importance in crisis management settings, due to its complex and dynamic nature (Hodgkinson & Healey, 2011). Yet, the idea that balance between cognitive styles may be ideal, regardless of the balanced score being high or low, is fairly new. In this new landscape, we want to take a closer look at this idea and ask the question: To what extent does balance between cognitive styles explain variation in task performance in a simulated crisis management setting? To explore this question, we have developed three hypotheses aimed at different aspects of our research question. This will be done by introducing and assessing two new, more nuanced measures of balance: a medium level of intuitive and analytic cognitive style, and a variable to quantify balance.

We hope that the findings of our analyses can contribute to an increased understanding of the role of balance between cognitive styles in decision-making, and, as such, be a part of filling the current research gaps (Appelt et al., 2011). Furthermore, we believe that the findings may be a step in better understanding and predicting how individual differences in cognitive style affect crisis management, which in turn can lead to improved mitigation, preparedness, response, and recovery of the crises of tomorrow.

2. Literature review

In the following literature review, we will discuss some of the relevant theories and research findings in the field of cognitive styles and crisis management. Firstly, we will begin by outlining the two overall approaches to decision-making: the dual-process and unimodel perspectives, and consequently, our theoretical stance on this matter. This is followed by a discussion of the effectiveness of intuition and analysis, particularly in a crisis management setting. In accordance with our dual-process perspective, we proceed by discussing the interaction between intuition and analysis, and the different combinations of cognitive styles that appear as a result.

2.1 Intuition and analysis

2.1.1 Unimodel vs. dual-process perspective

From simple day-to-day decision-making to extraordinary crisis management, effective decision-making requires the navigation of a range of information in order to select the alternative most likely to yield advantageous outcomes (Fletcher et al., 2012). Dual-process theorists posit that such decision-making involves the interaction of two distinct information-processing systems: intuition and analysis (Evans, 2008; Fletcher et al., 2012). Many labels (Table 1) and attributes (Table 2) has been used to describe these two modes of thinking. However, most authors agree on a distinction between one that is fast, unconscious, and high capacity, and one that is slow, conscious, and low capacity (Evans, 2008; Evans & Stanovich, 2013a). From a dual-process perspective, these two modes are assumed to operate in a parallel and interactive manner (Pacini & Epstein, 1999; Stanovich & West, 2000). That is, behavior is seen as a joint function of both modes, although their individual contribution can vary along a continuum from none at all to complete dominance (Stanovich & West, 2000).

Table 1: *A selection of labels associated with dual-process theories*

Intuition	Analysis	References
Automatic	Controlled	Schneider & Shiffrin (1977) Lord & Foti (1986, p. 21)
System 1	System 2	Stanovich (1999, p. 144) Kahneman & Frederick (2002)
Type 1	Type 2	Evans & Stanovich (2013a)
Reflexive (X-system)	Reflective (C-system)	Lieberman (2003)
Experiential	Rational	Epstein (1973)
Intuitive cognition	Analytic cognition	Hammond (1996, p. 8)
Associative system	Rule-based system	Sloman (1996)

Table 2: *A selection of attributes associated with the two cognitive systems*

Intuition	Analysis	References
Automatic, effortless, associative, rapid, parallel, affective, concrete, holistic, associative connections, slower to change, evolutionary old	Controlled, effortful, rule-based, slow, serial, neutral, abstract, analytic, reality oriented, logical connections, changes more rapidly, evolutionary recent	Kahneman & Frederick (2002) Epstein (1994) Norris & Epstein (2011) Sloman (1996)

Notwithstanding, not all theorists agree on this notion. Some argue in favor of a bipolar or "unimodel" approach, where intuition and analysis represents opposite ends of the same continuum (e.g., Keren & Schul, 2009; Kruglanski & Gigerenzer, 2011; Osman, 2004). Critics have questioned the dual-process perspective by arguing for a lack of theoretical coherence, which in turn makes it difficult to obtain empirical support for the assumptions made (Keren & Schul, 2009). For instance, Keren & Schul (2009) argue that researchers within the dual-process perspective have failed to establish clear norms for hypothesis testing, and point to the many different labels attached to the two information-processing styles (Table 1). Not only does this break the scientific principle of parsimony, but it can at times be misleading (Evans & Stanovich, 2013a; Hodgkinson & Sadler-Smith, 2018). For instance, many use the generic terms System 1 and System 2 proposed by Stanovich (1999, p. 144), which might falsely imply that there are exactly two singular systems underlying the two types of information-processing. In actuality, they each refer to a diverse set of cognitive systems. A second line of criticism lies in the observation that different attributes are not always observed in accordance with their assigned categories (Table 2) (Keren & Schul, 2009). For instance, some theorists make a distinction between intuition as unconscious and analysis as conscious (e.g., Dane & Pratt, 2007; Dijksterhuis & Nordgren, 2006; Pacini & Epstein, 1999), however, both information-processing systems can possess conscious and unconscious aspects (Evans & Stanovich, 2013a). Keren & Schul (2009) suggest that this contradicts the condition of isolability, which is required to establish their independence. Instead, they point to how different attributes are often assumed continuous, rather than intrinsically dichotomized. Dual-process theorists have countered this critique by emphasizing that the majority of the attributes are correlates that tend to occur with their prescribed category, and not necessarily defining characteristics (Evans & Stanovich, 2013a; Evans & Stanovich, 2013b).

Although a full review of this debate is outside the scope of this thesis, we believe that the fundamental assumption raised by dual-process theorists regarding the independence of intuition and analysis withstands the criticism raised.

Firstly, numerous studies have confirmed their orthogonal relationship, supporting the assumptions that intuition and analysis are independent constructs (e.g., Epstein et al., 1996; Norris & Epstein, 2011; Wang et al., 2017). Furthermore, several researchers have found significant interaction effects between intuition and analysis, further supporting their independent relationship (e.g., Pacini & Epstein, 1999; Handley et al., 2000, p. 104; Wang et al., 2017). Lastly, Evans (2008) argues that the strongest basis for a dual-process distinction comes from neuroscientific evidence indicating that the two information-processing systems can be mapped neurologically. For instance, Lieberman (2003; 2007) identified two systems: A reflexive (X-system) and reflective (C-system). The X-system is composed of amygdala, basal ganglia, and lateral temporal cortex, and has been associated with implicit and automatic cognitive processes, such as conditioning and associative learning. The C-system consists of areas associated with executive functioning, such as anterior cingulate cortex, prefrontal cortex, and medial-temporal lobe (Lieberman, 2003; Evans, 2008). Conclusively, although the dual-process perspective might have benefitted from a less proliferated development (Evans & Stanovich, 2013a) and more theoretical coherence (Keren & Schul, 2009), we believe there is sound evidence that the two information-processing styles operate independently. Subsequently, our overall approach to decision-making in this thesis will begin by taking a dual-process stance.

2.1.2 Intuition

Dane & Pratt (2007) defines intuition as affectively charged judgements that emerge from quick, unconscious, and holistic associations. Firstly, they are unconscious, in that the process of intuitive cognition is unconscious. The outcome of intuition, on the other hand, is often manifested as feelings and within the realms of conscious awareness (Dane & Pratt, 2007; Evans, 2010). The affective component is also reflected in our everyday language, such as implying that we have a "gut feeling" (Dane & Pratt, 2007). What is unconscious, however, is how the individual reached that specific inference or how they justify it (Dane & Pratt, 2007; Evans, 2010). In essence, this is what Hodgkinson et al. (2009) refers to when they describe intuition as "knowing" without knowing exactly why. Another central characteristic of intuition is that it is considered fast and capable of managing a high-capacity load (Lord & Foti, 1986, p. 21). As the intuitive processing does not require much attention nor control, the individual can quickly and automatically process several sequences in parallel without much interference (Schneider & Shiffrin, 1977). Intuition is also often described as being associative, in which different elements are linked in a holistic manner to recognize patterns and features (Dane & Pratt, 2007; Klein, 1998, p. 30). Intuition is, however, not acquired in a vacuum, such that these patterns and associations are often a product of previous learning and experience (Hodgkinson et al., 2009). This aspect of intuition is particularly evident in Klein's (2003, p. 4) definition of intuition as an extension of experience; it is our experience that enables us to recognize patterns and quickly react without a conscious awareness.

2.1.3 Analysis

Evans (2010) argues that analysis can be viewed as roughly the contrast of intuition. From this point of view, we already know a great amount about analysis: it is slow, conscious, controlled, and high-effort (Alaybek et al., 2021a; Evans, 2010). Rather than operating automatically and unconsciously, analytic thinking requires a deliberately controlled and intentional justification through logic and evidence (Wang et al., 2017). Closely linked to working memory capacity, analytic thinking has been associated with a range of higher order executive functions such as deductive reasoning, planning, and consequential decision-making (Evans, 2010). However, in alignment with Simon's (1997, p. 291) concept of bounded rationality, we have a limited capacity to execute and attend to these functions, making the process capacity-limited and slow (Schneider & Shiffrin, 1977; Lord & Foti, 1986, p. 21). Due to the cognitive burden, analysis takes place in a sequential rather than parallel manner, in which the individual must attend to one sequence at a time (Schneider & Shiffrin, 1977).

2.1.4 Intuition and analysis in crisis management

There is a debate amongst theorists in regards to the effectiveness of intuitive and analytic information-processing in decision-making (Bakken et al., n.d.). Historically, scholars and practitioners have emphasized the importance of logical reasoning as means to achieve rationality, in which analysis was seen as the only legitimate contributor to sound decision-making (Evans, 2010; Sayegh et al., 2004).

Intuitive processing, and particularly the affective component, was perceived as something that muddied the waters and should therefore be excluded from the whole decision-making process (Sayegh et al., 2004). Along the same lines, theorists within the heuristics and biases approach usually have a dismal portrayal of individuals' decision-making competences, often emphasized by the systematic errors and biases that might occur as a result of intuitive thinking (Hertwig & Grüne-Yanoff, 2017; Tversky & Kahneman, 1974). Primacy is therefore given to analysis, which has the function of controlling for these human fallacies (Kahneman & Klein, 2009). Contrary, a more recent trend has emerged where theorists now stress the importance of intuition instead (e.g., Gigerenzer, 2000; Klein, 1998; 2003; Sayegh et al., 2004). For instance, scholars within the naturalistic decision making (NDM) approach usually highlight circumstances where intuition poses as a powerful tool, such as when individuals have the possibility to receive effective feedback and recognizable learning opportunities (Klein, 1997, 1998, p. 28). On a similarly positive note, Gigerenzer (2000, p. 105) emphasizes how heuristics can be "fast and frugal" in ecologically rational situations. From a dual-process perspective, however, neither information-processing style is superior to the other. Rather, evidence suggests that intuition and analysis both have certain advantages and disadvantages depending on the context in which they are employed (Evans, 2010). Thus, a more accurate discussion can be obtained by analyzing their effectiveness, specifically in crisis management situations.

Crisis management situations are often characterized by three fundamental elements. Firstly, they are often represented by high stakes, where a faulty decision can result in major consequences. Secondly, the situation is often time restricted and requires rapid decisions. Lastly, the occurrence of the crisis is often unexpected or unanticipated (Seeger et al., 2003, p. 8; Sayegh et al., 2004). The use of intuition in these situations offers the apparent benefit of being quick, an element that might be determining in crisis management (Sayegh et al., 2004). Further, as the process is often automatic, the individual can choose to allocate their resources on other critical tasks (Lord & Foti, 1986, p. 38). Additionally, research within the NDM approach has generally focused on field settings characterized by time pressure, high stakes and dynamic conditions (Klein, 1998, p. 4-6) – situations similar to that of crisis management. Klein (1998, p. 161-162) developed The Recognition-Primed Decision Model (RPD) to explain how experienced decision-makers cope with time pressure. His findings were, amongst other, based on studies of fireground commanders' decision-making. When a crisis emerged, the fireground commanders did not seem to compare any options. Rather, they engaged in mental simulations that enabled them to envision a scenario and the potential consequences of a decision (Klein, 2003, p. 25-26).

However, as previously mentioned, in order to build effective mental simulations and recognize patterns and associations, individuals need to have relevant experience (Klein, 2003, p. 27; Hodgkinson et al., 2009). This highlights an aspect of intuition that could potentially pose a limitation in crisis management. Intuition and analysis have often been portrayed as a trade-off between speed and accuracy, in which the trade-off can be avoided by using intuition appropriately and thus making quick *and* accurate judgements. However, the mere use of intuition does not guarantee this leverage. The effectiveness of intuition depends on whether the individual has developed cognitive schemas that are domain relevant through experience and learning (Dane & Pratt, 2007). Similarly, Hogarth (2005, p. 71) argue that the quality of intuition depends on whether it was acquired in a "kind" or "wicked" environment, which in turn depends on whether the feedback is relevant or irrelevant, and whether the task is lenient or exacting (Hogarth, 2001, p. 217). One can argue that crisis management settings are often exacting, as the potential consequence of error is detrimental and thus require highly accurate judgements. However, Hogarth (2001, p. 89) further argues that exacting tasks combined with irrelevant feedback can be quite dangerous. If the individual is not aware of an error, the outcome might in fact reinforce their erroneous judgment and confidence. Thus, intuition might be a limitation in crisis management settings that are unexpected in regard to characteristics, or when relevant feedback is not provided. Consequently, if intuition is applied inappropriately, the individual might retrieve a quick, *but* inaccurate decision.

Analysis, on the other hand, is associated with greater accuracy – an attribute that is particularly valuable in a crisis management setting where the stakes are high (Dane & Pratt, 2007). Further, contrary to intuition, analysis is quick to change. Intuition requires repetitive and intense training to change pre-established schemas and habitual responses, whereas analysis changes with the speed of thought. Due to this, analysis could be particularly advantageous in crisis management settings where novel characteristics require rapid learning (Norris & Epstein, 2011;

Schneider & Chein, 2003). However, similar to intuition, analysis also has certain limitations. For instance, analytic processing is assumed to be less robust to different stressors (Schneider & Chein, 2003). As they require more control and attention, the slow and vulnerable processing can be particularly unfeasible under time pressure. Some theorists even argue that analysis might hinder the effectiveness of intuition (Dane & Pratt, 2007). For instance, analytic methods might interfere with intuition and cause what Klein (2003, p. 77-78) referred to as information "bottlenecks" that slow down the cognitive process.

Conclusively, the theoretical literature suggests that both analysis and intuition come with certain strengths and limitations in a crisis management setting, and none is clearly favored over the other. A more precise understanding of their effectiveness might be attained by considering a more interactionist perspective. In alignment with a dual-process perspective, this brings us to the next section of this thesis: the interaction between intuition and analysis.

2.2 The interaction between intuition and analysis

While we have now discussed the concepts of intuition and analysis in general, this thesis aims to explore the influence of balance between different combinations of intuitive and analytic styles. In order to do this, we will employ two theoretical frameworks accounting for the interaction between intuition and analysis, which is theorized to be the core component of cognitive styles (e.g., Epstein, 1994; Hodgkinson & Clarke, 2007). These are the Cognitive-Experiential Self-Theory (CEST) by Epstein (1973, 1994) and Hodgkinson and Clarke's (2007) 2x2 grid of cognitive style combinations.

2.2.1 CEST

CEST, developed by Epstein (1973, 1994), is one of the most influential and recognized theories of cognitive style (Akinci & Sadler-Smith, 2013). This dual process theory of personality pivots on the experiential (intuitive) and rational (analytic) systems (Epstein, 1994). The experiential and rational systems share many of the characteristics mentioned with respect to intuition and analysis. The experiential system can be described as holistic, associative, affective, rapid, but slower to change, influenced by past experience, passive and preconscious. Conversely, the rational system can be described as analytic, logical, evidence-based, conscious, slower in processing and more rapid to change (Epstein, 1973, 1994).

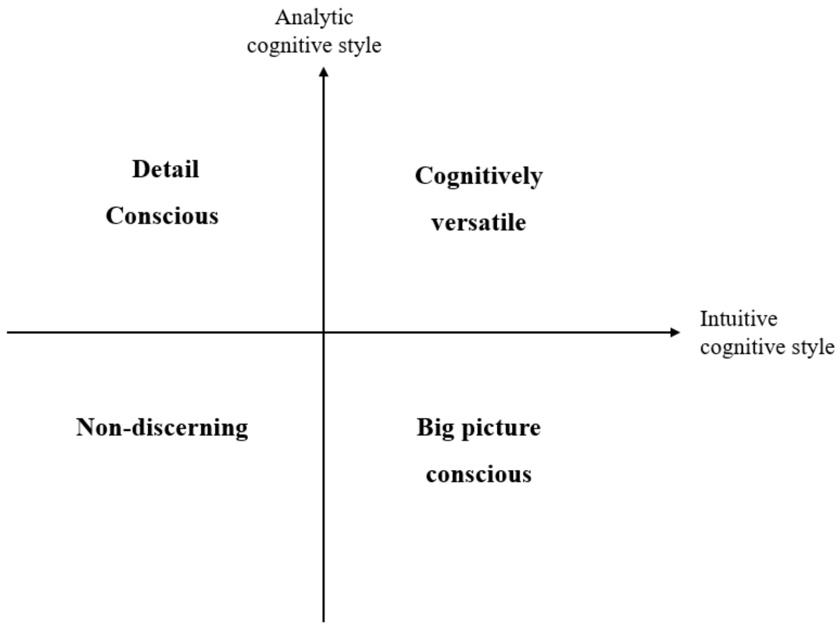
In addition to describing the two systems, CEST accounts for the preference one has for them. One can differentiate between cognitive style and cognitive processing (Sinclair & Ashkanasy, 2005: Bakken, 2013), where the former is a preference and the latter refers to the utilization of a certain information-processing mode (Sinclair & Ashkanasy, 2005). Thus, cognitive style does not pertain to one's objectively measured ability to use analysis or intuition, but one's preference for analytic and intuitive cognition.

Another important aspect of CEST is the emphasis it puts on interaction, as all behavior is assumed to arise from the interaction between the two systems (Epstein, 1994). The two systems work independently through cooperation and competition (Epstein, 1994, 1998, p. 224; Epstein et al., 1996, 1999; Pacini et al., 1998; Pacini & Epstein, 1999). At some point, the two systems compete, often exemplified as a struggle between the head and the heart. At other times, one system might dominate, and has complete control over the decision making (Epstein, 1994; Epstein et al., 1996, 1999; Pacini et al., 1998; Pacini & Epstein, 1999). Their relative dominance may, however, vary depending on situational demands and individual characteristics, such as the person's preference for a system. Based on the interactive and independent characteristics of the two systems, Epstein (1998, p. 233) postulates that individuals can score either high or low on both the experiential and the rational system, resulting in four different combinations of cognitive style: low-low, low-high, high-low and high-high. However, Epstein (1998) does not further theorize about the combinations' effects on individual behavior. This brings us to our next theoretical framework

2.2.2 Hodgkinson and Clarke's (2007) 2x2 grid

While Epstein (1994; 1998, p. 233) argues that the interaction between analysis and intuition is important, Hodgkinson and Clarke (2007) illustrated this interaction more concretely by sketching out a 2x2 grid model of possible combinations, with their predicted influence on performance. This theory builds on work by several other researchers and theorists (e.g., Langley, 1995; Clarke & Mackaness, 2001; Klein, 2003). An illustration of the grid is represented in Figure 1. These categories are: detail conscious (low preference for intuition and high for analysis), big picture conscious (high preference for intuition and low for analysis), non-discerning (low preference for both intuition and analysis) and cognitively versatile (high preference for both intuition and analysis).

Figure 1: *Hodgkinson & Clarke, 2007 (edited illustration)*



The detail conscious are assumed to approach decision-making systematically in a step-by-step process, and subsequently they might lose perspective on the larger picture (Hodgkinson & Clarke, 2007). They are also theorized to become obsessive in their focus on numbers, analyses and reports (Langley, 1995). Similar to Klein's (2003, p. 77-78) proposition, it is argued that these individuals might perform worse in situations characterized by stress and time pressure, as analytic thinking can cause a bottleneck for intuitive processing (Hodgkinson & Clarke, 2007). Conversely, the big picture conscious can have difficulty focusing on the finer details, thus, possibly overlooking important features others might notice (Clarke & Mackaness, 2001). The big picture conscious bear resemblance to Langley's (1995) "extinction by instinct", where decisions are devoid of analytic reasoning, relying purely on emotion (Clarke & Mackaness, 2001).

In contrast, the non-discerning are generally assumed to use as little cognitive resources as possible. Some argue that they simply do not like to think, and thus rely on the insights of others instead of their own analysis and intuition

(Hodgkinson & Clarke, 2007). Some have gone as far as to label this category of combination "poor thinking" (Shiloh et al., 2002). The cognitively versatile, on the other hand, are theorized to deploy both analysis and intuition when necessary. They are assumed able to focus on details when the situation requires them to, and the big picture when this is necessary. Accordingly, they are assumedly able to switch more readily than the three other categories (Hodgkinson & Clarke, 2007).

2.2.3 Combining theory and research on interaction effects

Bakken et al. (n.d.) conducted a study to examine the interaction effects of intuitive and analytic cognitive style on task performance in a simulated crisis management setting. When studying intuitive and analytic cognitive style in isolation, they did not find any significant main effects on task performance. However, they did find a significant interaction effect, both when the tasks were conducted on an individual level (standardized $\beta = .70$, $p < .05$) and on a team level (standardized $\beta = .43$, $p < .001$). Although dual-process theorists have long suggested that intuition and analysis work in a parallel and interactive manner (e.g., Stanovich & West 2000; Pacini & Epstein, 1999), research examining interaction effects has been scant (Bakken et al., n.d.). These findings underscore the importance of increased research on the interaction between intuitive and analytic cognitive styles.

Given that intuition and analysis interact in their influence on behavior, one can ask whether certain combinations are more advantageous than others (Bakken et al., n.d.). When looking at specific combinations of cognitive styles, Bakken et al. (n.d.) found the combination of high intuition and high analysis to yield the best task performance. This is not particularly unexpected, and well in accordance with previous theory. For instance, by interpreting this in light of Hodgkinson and Clarke's (2007) 2x2 grid, individuals scoring high on both intuition and analysis would be positioned within the "cognitively versatile" category: the category seen as most valuable for strategic decision-making, due to their ability to adapt and switch from one mode to another (Hodgkinson & Clarke, 2007; Hodgkinson et al., 2009). More unexpected, however, is the finding that individuals scoring a low preference for both intuition and analysis had an equally good performance as those scoring high on both (Bakken et al., n.d.). In contrast, Hodgkinson and Clarke (2007) suggested that these individuals are likely to exhibit poor judgment as they deploy minimal cognitive efforts. In addition to the findings that high-high and low-low combinations yielded similarly good task performance, Bakken et al. (n.d.)

found that combinations represented by one dominant mode (high-low or low-high) were associated with substantially lower task performance. Overall, these findings led Bakken et al. (n.d.) to suggest that individuals with a balanced cognitive style (high-high or low-low) performed better than individuals with a dominant cognitive style (high-low or low-high) due to increased cognitive flexibility.

Cognitive flexibility has received a substantial amount of attention prior to these findings (e.g., Louis & Sutton, 1991; Epstein, 1994; Hodgkinson & Clarke, 2007). For instance, several theorists have raised attention to the ecological validity of a mode, and the fact that the effectiveness of a mode is a function of the match between mode and task demands (Dunwoody et al., 2000; Louis & Sutton, 1991; Kruglanski & Gigerenzer, 2011). In other words, neither intuition nor analysis is superior to the other; it is dependent on the match between mode and task (Kruglanski & Gigerenzer, 2011). Strategic decision-making is therefore achieved when an individual is able to sense when a switch is needed, and thereon alternates to the appropriate mode (Hodgkinson et al., 2009). The ability to be cognitively flexible and to adapt can be advantageous in many situations, particularly in situations that are highly complex and dynamic, such as in crisis management (Hodgkinson & Healey, 2011). Additionally, given the advantages and disadvantages of intuition and analysis, it follows that an interaction where complementarities are exploited is valuable. Thus, compared to individuals with a dominant preference, individuals with a balanced preference might be able to utilize a more diverse repertoire of strategies and more easily “shift gears" when required (Louis & Sutton, 1991; Bakken et al., n.d.). Contrary, those who are devoted to a certain mode might be more prone to cognitive inertia, in which they are overly dependent on either intuition or analysis, and thus fails to notice and adapt to changes (Laureiro-Martínez & Brusoni, 2018; Hodgkinson, 1997). This is similar to what Langley (1995) refers to as two deadly extremes; “paralysis by analysis” and “extinction by instinct”. Conclusively, there seems to be a great deal of theoretical support for the notion that cognitive flexibility is advantageous. Nevertheless, we have proposed the findings of Bakken et al. (n.d.) to form a new landscape.

Looking at the findings of Bakken et al. (n.d.) with respect to previous theoretical contributions, the discrepancy does not seem to be that we have not acknowledged the benefits of being balanced. Certainly, numerous theorists have proposed this for some time (e.g., Louis & Sutton, 1991; Epstein, 1994; Hodgkinson & Clarke, 2007). However, the difference seems to be that theorist, such as Hodgkinson & Clarke (2007), have not *interpreted* the low-low combination as equally "cognitively versatile" as the high-high combination, and consequently gaining the same benefits. A low preference for intuition and analysis might not imply that those individuals do not like to think, as previously assumed (Hodgkinson & Clarke, 2007; Hodgkinson et al., 2009). Rather, it might imply that they do not have a preference for *how* they think (Bakken et al., n.d.). Nevertheless, they can still "bend and flex" given their balanced, albeit low, preference. This possible misinterpretation might be due to a central problem within the field where cognitive style is directly translated to cognitive processing (Sinclair & Ashkanasy, 2005; Bakken, 2013). As previously mentioned, while cognitive style refers to a dispositional preference, cognitive processing refers to the actual use of an information-processing mode (Sinclair & Ashkanasy, 2005). Thus, a low score on a cognitive style is indicative of that person's preference, and may not necessarily mean that they employ little processing (e.g., Bakken et al., n.d.).

The findings of Bakken et al. (n.d.) could also have an alternative explanation. Rather than the key mechanism being cognitive flexibility to shift between the two modes, it could potentially be an increased awareness of situational cues. Shiloh et al., (2002) conducted an experiment where they examined the interactive influence of intuitive and analytic cognitive style on framing effects. The framing effect refers to decision-makers' tendency to respond differently to objectively similar, but differently framed decisions (Levin et al., 1998). Similar to Bakken et al., (n.d.), Shiloh et al., (2002) found no significant main effect of intuitive and analytic cognitive style, but a significant interaction effect. However, the framing effect was only found in two combinations of cognitive style: high-high and low-low. As a possible explanation, the authors suggested that individuals with a dominant cognitive style might be less susceptible to framing effects due to their strong internal guides. Contrary, individuals with a balanced preference do not have the same strong internal guide and might therefore rely more on situational cues, such as the framing of the decision. Although framing effects and other biases are often associated with fallacies (Kahneman, 2013, p. 13), being sensitive to situational cues might be advantageous in crisis management. For instance, Klein (2003, p. 24-35) suggests that situation awareness makes us drawn to certain cues and not others, which firstly prevents information overload, and secondly, forms the basis for recognizing patterns. As individuals with a balanced cognitive style are found to (a) have a higher task performance in a simulated crisis management setting and (b) be more susceptible to framing effects, we argue that they might be influenced by a common main mechanism: increased sensitivity to situational cues.

A third possible main mechanism behind the findings of Bakken et al. (n.d.) is "paradox reconciliation". Calabretta et al. (2017) conceptualizes intuition and analysis as a paradoxical tension, in an attempt to account for the interplay between the two modes. Intuition and analysis are different information-processing approaches and constitute in many ways a contradiction (e.g., fast vs. slow, automatic vs. controlled). This paradox is not fully solvable (Calabretta et al., 2017), yet theory and research points to the importance of combining both modes to achieve strategic decision making (e.g., Hodgkinson et al., 2009; Bakken et al., n.d.). Thus, Calabretta et al. (2017) argues that by being able to manage, rather than eliminate the paradox, a decision-maker can leverage the complementarities of both modes. For instance, one can engage in paradoxical thinking by finding linkages that accommodate both intuition and analysis (Smith, 2014), or by attempting to recognize distinct benefits of both modes and utilize them separately (Jay, 2013; Calabretta et al., 2017). In their study of the development of innovation outcomes, Calabretta et al. (2017) found that individuals who engaged in such paradoxical thinking were able to manage the competing requirements of both financial (e.g., sales, productivity) and non-financial (e.g., visual appeal, brand values) goals. Thus, the findings of Bakken et al., (n.d.) can also be interpreted in light of this, in which individuals with a balanced preference might more easily reconcile the paradoxical tension between intuition and analysis, and thus exploiting both modes, compared to those who are inclined towards a dominant mode.

Although the focal point of this thesis is to further examine the findings of Bakken et al. (n.d.), we have proposed additional main mechanisms that could be theoretically applicable. Nonetheless, they all seem to build on a common denominator where balance is advantageous. Thus, it follows that support for the importance of balance between cognitive styles in predicting task performance, would in fact support all of the main mechanisms proposed. This brings us to our next section, our hypotheses.

2.3 Our hypotheses:

Based on the findings of Bakken et al. (n.d.), we want to examine the extent to which balance between cognitive styles explain variations in task performance in a simulated crisis management setting. As mentioned, Bakken et al. (n.d.) argued that balance between cognitive styles, regardless of the style per se, might be a predictor of task performance. For simplicity, we label this theory the balance theory. In order to examine this theory, we have developed three hypotheses. These are all aimed to answer our research question by studying different aspects of the balance theory. This will be done by introducing and assessing two new, more nuanced measures of balance: a medium level of intuitive and analytic cognitive style, and a directional difference score.

2.3.1 Hypothesis 1

Bakken et al. (n.d.) found that individuals with a balanced cognitive style (high-high or low-low) performed better than individuals with a dominant cognitive style (high-low or low-high). Further, the main mechanism proposed was increased cognitive flexibility. Individuals with a balanced cognitive style are assumed to be more adaptable and able to switch between their diverse repertoire of strategies, as compared to individuals with a dominant cognitive style. In a crisis management setting, this ability to easily switch can be of particular importance, due to the complex and dynamic nature of crisis management (Hodgkinson & Healey, 2011).

In order to examine the extent to which balance between cognitive styles explains variations in a simulated crisis management setting, we want to introduce a new level of cognitive style, namely a medium level. We begin by conducting the same analyses as Bakken et al. (n.d.); a regression analysis followed by a simple slope analysis, but now with an additional third medium slope to examine the balance theory with additional nuance. An interesting finding from their simple slope analysis is that it indicated a hypothetical medium-medium combination to perform less advantageous than the high-high and low-low combinations. This is due to the crossing point between the two slopes of the analysis being in the middle. However, it is important to note that they did not explicitly study the medium-medium combination. Therefore, one cannot fully make conclusions about the medium-medium combination from their simple slope analysis.

If balanced cognitive styles are more advantageous than dominant cognitive styles, then it follows that medium-medium combinations should perform equally well as the high-high and low-low combinations. Alternatively, a medium-medium combination might not follow the exact same principles, indicating that contingencies exist, and nuances should be considered. Based on this, our first hypothesis is as follows:

H1: Those who score medium-medium will perform equally well in a simulated crisis management setting, to those who score high-high and low-low on intuitive and analytic cognitive styles.

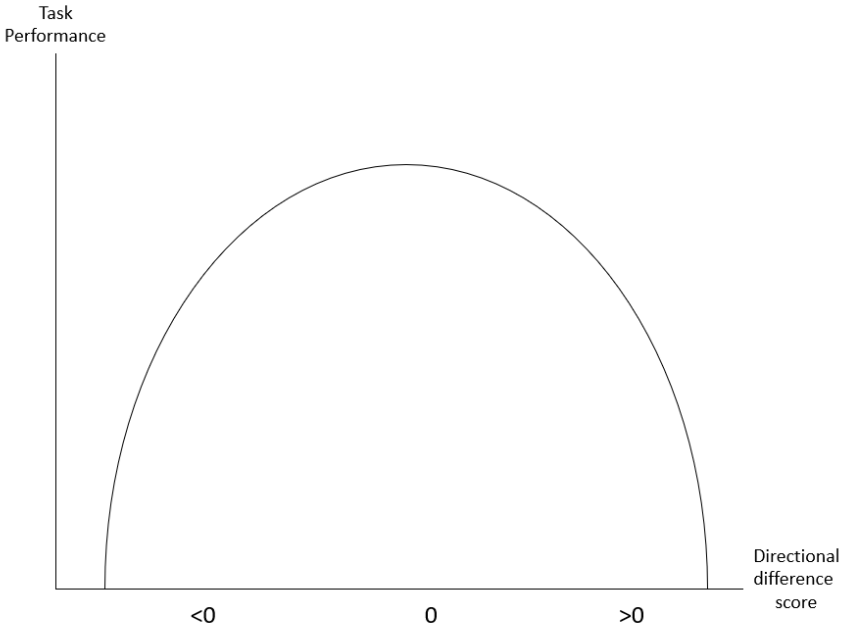
2.3.2 Hypothesis 2

In our second hypothesis, we will look further into the balance theory and its predictive power on task performance in a simulated crisis management situation. Behind the theory of balance lies the assumption that the more balance one has, the better one will perform. In order to quantify balance, we have created a directional difference score (d=ACS-ICS), by subtracting intuitive cognitive style (ICS) from analytic cognitive style (ACS). Thus, those with a directional difference score of 0 is expected to perform the best, as they are measured to have perfect balance between the two styles. The directional difference score also allows one to see whether a candidate prefers intuition or analysis. An individual who has a directional difference score of >0 can be described as predominantly analytic, as their score on analysis would be higher than intuition. Conversely, an individual with a directional difference score of <0 would be predominately intuitive, as their score on intuition would be higher than analysis.

This hypothetical relationship between the directional difference score and task performance is illustrated in Figure 2. The y-axis portrays task performance and the x-axis portrays the directional difference score. Here, those who score a clear preference for intuitive style would be positioned to the left relative to 0, whilst those who clearly favor analysis are on the right. Those with a balanced approach are placed in the middle, at around zero. Further, the relationship would be assumed curvilinear, which portrays those with a predominantly intuitive or analytic style to perform poorest. Conversely, those who are perfectly balanced, with the exact same preference for intuition and analysis, perform the absolute best.

It is important to note here that this is just a model of the assumption, and as such purely hypothetical and illustrative.

Figure 2: *The assumed negative quadratic relationship between directional difference score and task performance. (Note: only illustrative and hypothetical)*



We believe that this directional difference score is of particular interest when studying the potential effects of balance, as it shows the directionality of candidates' preference. This is important as the slope might not be perfectly symmetrical. Bakken et al. (n.d.) found that having a preference for intuition was more advantageous than having a preference for analysis, despite both being inferior to the balanced low-low and high-high combinations. Further, Mohaghegh and Größler (2020) found that the best strategy was one where 70% of the cognitive resources were allocated on analytic thinking, and 30% on intuitive thinking. This goes, in part, against the assumption portrayed in Figure 2, as it would cause the slope to skew to the right. Such a skew would be an interesting find, as it could easily go unnoticed due to cognitive styles being frequently studied as categorical variable instead of ordinal or continuous (Fletcher et al, 2012). For the balance theory to hold true, the regression equation will not drastically skew to one side or the other. Rather the maximum value of the negative quadratic regression equation of the directional difference score should be at approximately zero ($d \approx 0$): indicating perfect balance between intuition and analysis as the ideal.

We further believe that studying this slope is important in regards to the results of hypothesis 1; if it is true that the medium-medium combination is associated with lower performance compared to their other balanced counterparts, it is likely to impact this regression equation. It is, however, difficult to predict in what way and to what extent. While the medium-medium combination might score lower than high-high and low-low, they might still perform better than those with a dominant approach. Subsequently, a rejection of hypothesis 1 could cause the slope to change completely, or simply flatten the curve slightly, depending on the performance of the medium-medium combinations. However, rejecting hypothesis 1 would not automatically cause rejection of this hypothesis. Thus, we believe that this hypothesis is interesting independent of the findings from hypothesis 1.

These points lead us to hypothesis 2a:

H2a: *The relationship between the directional difference score and task performance in a simulated crisis management setting follows the slope of a negative quadratic* regression equation, *with a maximum value at approximately d=0.*

After examining whether medium-medium combinations perform as expected according to the balance theory, and whether the relationship between the directional difference score and task performance is as the balance theory predicts, we will move on to assess the predictive power of balance between cognitive styles. This is important, as there can be evidence for a theory to be true, without it holding predictive power. The predictive power is imperative to the potential usefulness of the theory, as it can then be utilized for practical purposes. Furthermore, if balance is an important predictor of task performance in crisis management, above what control variables, main effects and their interaction term might provide, the potential practical implications of balance between cognitive styles is underscored.

Based on the directional difference score created in hypothesis 2a, we will create a model which accounts for control variables, intuitive and analytic cognitive style and the directional difference score. If the regression equation is found to be quadratic in hypothesis 2b, the directional difference score will be squared in this model. We label this model the difference model. The predictive validity of this difference model will be compared with the more established model containing control variables, intuitive and analytic cognitive style, and their interaction term.

For simplicity, we will call this latter model the interaction model. It is important to note here, that while balance entails a form of interaction, the word interaction in this hypothesis refers specifically to the interaction term. Further, the reason for comparing the difference model with the interaction model, is that the inclusion of an interaction term is more commonly used in cognitive style research (e.g., Bakken et al., n.d.; Mahoney et al., 2011).

These points lead us to our last hypothesis:

H2b: *The difference model explains more variation in task performance in a simulated crisis management setting, than the interaction model.*

This last hypothesis is somewhat dependent on both hypothesis 1 and 2a, as it is highly unlikely that balance predicts performance if both hypothesis 1 and 2a are rejected. Thus, the exploration of this hypothesis is only relevant if at least one of the two previous hypotheses are confirmed.

3. Research Method

3.1 Research strategy and design

The overarching research strategy for this thesis is a quantitative one, as we emphasize quantification when analyzing the data. Additionally, the data provided to us has also been collected with a quantitative approach (Bell et al., 2019, p. 35). As frequently associated with the quantitative approach, we employ a deductive approach to the relationship between theory and research by deducing hypotheses on the ground of existing theory, and further expose them to empirical examination (Bell et al., 2019, p. 20) However, as Bell and colleagues (2019, p. 23) has noted, deduction often entails an element of induction, and researchers usually infer implications of their findings with respect to the initial theory. This could be particularly relevant in our case, as the balance theory constitutes a relatively novel and understudied landscape (Bakken et al., n.d.).

We find the most appropriate description of this research design to be a mixed design (Bordens & Abbot, 2014, p. 326-327), albeit with some minor variations. Firstly, it contains between-subject observations, as each participant has provided data on each independent variable: both intuitive and analytic cognitive style. This is further combined with within-subject observations, as the original data contained each participant’s response to seven different tasks (Bordens & Abbot, 2014, p. 289). However, as we have only received the average of those tasks, our specific research design does not completely fulfill the requirements of the mixed design, specifically with respect to within-subject observations. Usually, a mixed design requires more complex statistical modeling (Kherad-Pajouh & Renaud, 2015). As there are no within-subject factors in our data set, we are able to utilize simpler statistical methods. It is also important to note that while mixed designs are frequently used in experiments and quasi-experiments (Kherad-Pajouh & Renaud, 2015), this particular research design cannot be defined as an experiment, as no manipulation has been involved.

3.2 Data collection

In working with this thesis, we were offered to work on existing data from the MindLab laboratory at BI, headed by Thorvald Hærem, our supervisor. The dependent variable is based on individuals’ task performance in a microworld specifically designed to simulate a crisis management setting. The participants physically attended BI and conducted the simulation within a classroom setting (Bakken, 2013). Although the simulation has had several iterations, including ones where individuals play within teams, our primary unit of measurement and analysis is individuals. In other words, the participants’ performance is solely dependent on their own accomplishment in the simulation. Prior to this participation, the individuals had also received questionnaires in order to collect data on cognitive style and control variables. It is also worth mentioning that the data set provided is previously used in study 1 of Bakken et al. (n.d.), in addition to Bakken (2013).

3.2.1 Ethics, GDPR and NSD

As the data has been previously gathered and analyzed (Bakken, 2013; Bakken et al., n.d.), the NSD has been contacted in regards to the gathering and use of the data which we have received. Furthermore, the data is completely anonymized, and as such do not contain any identifiable information. Consequently, concern regarding GDPR are not as relevant for this thesis. For these reasons, we have concluded with our supervisor that there is no need to contact the NSD.

As we are not collecting our own data, we also do not need to be as concerned with the ethical considerations of data collection. For example, consent has already been given by research subjects. However, there is always ethical concern with any research, irrespective of the data gathering process. This concern is more related to the impact of research and the responsibility we as producers of research findings hold as we analyze, reflect and draw inferences based on our findings. We have strived to choose the most accurate ways of data analysis, and to reflect the findings of these analyses in a transparent and accurate manner. Furthermore, we have considered any limitations and methodological issues carefully, which will be thoroughly examined in the discussion.

3.3 Sample

It is argued that an important factor influencing the power of a statistical analysis is the sample size. This is even more important when examining interaction effects, which requires a larger sample size to achieve the same power as examining main effects (Dawson, 2014). For instance, Shieh (2009) suggests a sample size of 137-154 for interaction effects, compared to 41 for simple correlations. Our sample size consists of 107 individuals, which might be a smaller sample than ideal. However, it was still shown sufficient to reveal interaction effects (Bakken, 2013; Bakken et al., n.d.). This might be attributed to other factors besides sample size that alleviates some of the issues known to attenuate the power of detecting interactions. For instance, Dawson (2014) advises the use of continuous variables rather than artificial categorization, which is used in the regression analysis in both hypothesis 1 and 2a.

Further, our sample of 107 individuals consists of 74 BI students (69.2%) and 33 military cadets (30.8%). All of the military cadets were, at the point of data collection, Second Lieutenants and during their first year of a bachelor’s program at a Norwegian military academy. This usually entails 3-4 years of operative experience in addition to military education (Bakken, 2013). The average age of participants is 23.7, with a maximum of 53 and a minimum of 19. Regarding gender, the sample consists of 29.9% female and 70.1% male participants. For further detail about age, gender and experience of participants, see Appendix A.

3.4 Measures

All of the measures discussed in this section were gathered by Hærem and colleagues at BI, and are therefore available for us to use in our data analysis. Our dependent variable is task performance, and our independent variables are intuitive and analytic cognitive style, or alternatively the directional difference score based on them, depending on the hypothesis. In addition, we have control variables for experience, cognitive ability and personality. In this section, all variables will be presented, and we will review two important quality characteristics of each; their reliability and validity. The reliability of a measure refers to its ability to produce similar results when repeated under identical circumstances, and validity refers to the extent it is able to measure what it is intended to measure (Bordens & Abbott, 2014, p. 126-129). When reviewing their reliability, we will mostly employ Cronbach's alpha as a test of internal reliability, which is generally recommended to be .70 and above (Bell et al., 2019, p. 173).

3.4.1 Task performance

Our dependent variable is task performance in a simulated crisis management setting. The crisis management setting is in the form of a microworld or a simplified computer simulated decision environment (Bakken, 2013). This is performed through the platform MindLab, developed by Thorvald Hærem and his colleagues in collaboration with the Norwegian Military and Appex AS.

During the simulation, individuals are required to make decisions under time pressure, efficiently collect information, accurately process that information, and allocate resources quickly and correctly. Thus, participants fail a task if they choose the wrong answer, or the answer is provided too late. The setting is therefore highly controlled and laboratory-like, as individuals engage in identically timed tasks, with the same resources and information available. However, there are also field-like components of the simulation, as the tasks are created to be conceptually similar to real life crisis management situations (Bakken, 2013). In fact, the content and nomological validity was established in cooperation with seven experts in the field of crisis management at the Norwegian Defense University College and Norwegian Military Academies. The tasks had also a Cronbach's alpha of .65 (Bakken, 2013), which is slightly lower than the .70 recommended, however, Kaufman et al. (2010) argue that a lower level of reliability is usually to be expected when measuring behavioral tasks.

There are three parts to the simulation. The first part pertains to rescue operations, the next to security operations and the last part is a combination of the prior two. The simulation contains twelve tasks, in which five are warm-up questions asked at the beginning of each section, whilst the remaining seven tasks are used to evaluate the participant's performance. Each task is scored between 0 and 1, where 0 indicates no correct decisions, whereas 1 indicates a perfect performance. The score on these seven tasks is further averaged, creating the overall performance score (Bakken, 2013).

3.4.2 Intuitive and analytic cognitive style

Our independent variables are intuitive and analytic cognitive style. These are measured by the corresponding experiential (intuitive) and rational (analytic) cognitive style, gathered through the self-reported Rational-Experiential Inventory of 40 items (REI-40) (Pacini & Epstein, 1999). The inventory measures the dimensions of experiential and rational processing on two subscales each: experiential ability, experiential engagement, rational ability, and rational engagement. Each subscale is measured by ten composite items, which has been averaged further into two scores. These items are on a 5-point Likert scale (Keaton, 2017, p. 531).

When it comes to reliability, the REI-40 inventory has Cronbach's alpha ranging from .77 to .91, (Keaton, 2017, p. 531), and is one of the most reliable and frequently utilized inventories for cognitive style (Phillips et al., 2016). In calculating the reliability for the REI-40 on our sample, we found the Cronbach's alpha to be .80 for rationality and .87 for experientiality, and thus well above the .70 limit suggested. The inventory has also shown evidence of both convergent and divergent validity (Pacini & Epstein, 1999), and empirical evidence that the two subscales are orthogonal as theoretically assumed (Handley et al., 2000, p. 104).

Another note of importance is the need for compatibility between cognitive style measure and theoretical positioning. For instance, single measure dimensions are compatible with a unimodel perspective, where one does not acknowledge a clear distinction between intuition and analysis (Philips et al., 2016). As mentioned, REI-40 is developed by Pacini and Epstein (1999), and based on CEST.

Consequently, they both follow a dual-process perspective, where intuition and analysis are seen as independent. Thus, we find the decision to utilize REI-40 to measure cognitive style to be clearly compatible with our theoretical positioning.

3.4.3 Balance between cognitive styles

Balance between cognitive styles was alternatively used as an independent variable, and quantified by creating a directional difference score. The directional difference score is derived from the REI-40 scores, in which the score on intuitive cognitive style is subtracted from the score on analytic cognitive style. This creates a range from -5 to 5, where -5 indicates a complete preference for intuition, and 5 a complete preference for analysis. Individuals with a perfectly balanced style will have a directional difference score of 0, indicating that their score on intuitive and analytical cognitive styles are identical.

3.4.4 Control variables

The control variables included in the analysis are personality, cognitive ability and experience. Based on previous research and theory, we find a clear rationale to control for all of these variables when examining the relationship between cognitive style and task performance. Personality, cognitive ability and experience have been previously shown to influence performance (e.g., Schmidt & Hunter, 1998; Van Iddekinge et al., 2018). Additionally, the control variables have also been directly related to cognitive style. (e.g., Alaybek et al., 2021b; Klein, 1998, p. 57; Okoli et al., 2016; Pretz, 2008)

Personality: Although the validity of personality traits seems to depend on the situation, conscientiousness has been shown to be a valid predictor of job performance across occupations (e.g., Schmidt & Hunter, 1998; Barrick & Mount, 1991). It is further assumed that cognitive style is rooted in personality, as it involves the tendency to perceive, think and behave in certain ways across situations (Alaybek et al., 2021b). Empirical evidence for this assumption has been provided by Pacini and Epstein (1999) who found The Big Five personality factors to explain 28-39% and 9-12% of the variance in analytic and intuitive cognitive style, respectively.

Data on personality was collected using a Big Five personality inventory, specifically the 60-item NEO-FFI inventory. This is a shorter version of the NEO PI-R inventory (Costa & McCrae, 1992, as cited in Bakken et al., n.d.). Although there exists a trade-off between internal reliability and scale length, measures of internal reliability still seem to be appropriate with this scale. For instance, Chapman (2007) found the five factors to yield a Cronbach's alpha ranging between .72 and .88.

Cognitive ability: Cognitive ability has been argued to be an important predictor of job performance, and its validity is shown generalizable across situations (Schmidt & Hunter, 1998; Schmitt, 2014). Cognitive style has also been assumed to be related to cognitive ability, as it concerns cognitive domains such as information-processing and decision-making (Alaybek et al., 2021b). For instance, Alaybek et al. (2021a) found that analytic cognitive style had a significant correlation of .23 with cognitive ability.

Cognitive ability has been measured using the Cattell Reasoning B-scale from Cattell's 16PF version 5 (OPP, 1994, as cited in Bakken et al., n.d.), which correlates with IQ measures (Cattell & Scherger, 2003, as cited in Bakken et al., n.d.). For instance, Abel and Brown (1998) found a correlation of .52 between the 16PF B-scale and WAIS-R full scale, indicating that it is a fair, although modest measure of cognitive ability. Bakken et al. (n.d.), used the sum of the raw scores, where one point was awarded for each correct answer on the test.

Experience: Lastly, experience has played a major role in the field of judgment and decision-making in general, and particularly with respect to expertise and expert intuition (e.g., Klein, 1998, p. 57; Okoli et al., 2016). Pretz (2008) examined the relationship between cognitive style, experience and problem-solving and found that the appropriateness of a cognitive style depends on the problem-solver's level of experience; analysis was found more appropriate for experienced individuals, while novices benefited more from an intuitive approach.

The control variable of experience was simply gathered for whether or not the individuals are business school students or military cadets. These two measures are dummy coded, 0 for the former and 1 for the latter. It is however important to note that the business school students could potentially have military experience, which is not accounted for.

4. Data analysis

In addition to reliability and validity, there is one more important quality criteria to account for: replicability. In order for replication to take place, procedures must be described in great detail (Bell et al., 2019, p. 46). Thus, as a means to ensure transparency, we will thoroughly describe the procedures and steps we have taken to reach our findings. First, we will discuss our general approach to data cleaning, screening and exploration, and further, we will explain the procedures conducted with respect to the specific hypotheses.

As the data provided has been previously used by Bakken et al. (n.d.) and Bakken (2013), it was also thoroughly cleaned prior to us receiving it. Thus, we did not observe any outliers or missing data. However, we still proceeded to screen the data for any deviant observations, both statistical and theoretical.

We also examined how our sample performed with respect to the analyses we had planned to conduct, and the assumptions they are based on. For instance, although we had planned to conduct a simple slope analysis for two-way linear interactions, we did examine if our dataset had any indications of a quadratic two-way interaction. We followed Dawson's (2014) advice and examined whether our independent variables squared (X^2) added any significant variance beyond the independent variable (X). We examined intuitive and analytic cognitive style and their multiplicative interaction term, and found that their squared counterpart did not add any significant difference. It is worth noting, however, that the squared analytic cognitive style was not far off (F change = .051). (See Appendix B for further detail).

Lastly, we also examined multicollinearity, particularly as one could expect intuitive and analytic cognitive style, and their interaction term to correlate with each other. As expected, The VIF-values (See Appendix C) for these variables ranged from .59 to 109.53, which is well above the 5 limit. The remaining variables had VIF-values well below the 5 limit, and were therefore not suffering from multicollinearity. Thus, before we proceeded with any of the statistical analyses, we mean-centered intuitive and analytic cognitive style to solve this issue. Additionally, we also followed Dawson's (2014) advice with respect to three further points. Firstly, we created our interaction term based on mean-centered intuitive and analytic cognitive style, and did not mean-center the interaction term itself. Secondly, we also mean-centered our control variables: the five personality variables and cognitive ability. However, we did not mean-center the experience variable, as it was a dummy variable in which zero constitutes a meaningful value. Lastly, the dependent variable, task performance, was also not mean-centered, as it could potentially fail to reflect true variation in our analysis (Dawson, 2014).

4.1 Hypothesis 1

In order to analyze the task performance of the medium-medium combination as compared to high-high and low-low combinations, we opted to conduct a similar simple slope analysis as that of Bakken et al. (2013) – but now introducing a medium-slope. The reason why we compare our analysis to Bakken (2013) and not Bakken (n.d.) is due to the fact that we use the aggregated scores of the 107 individuals, similar to Bakken (2013), whilst Bakken (n.d.) uses their single 749 observations and thus a repeated measures analysis.

Our first step was to perform the same regression analysis as Bakken et al. (2013) to obtain the information we needed for the simple slope analysis. Thus, we conducted a hierarchical regression analysis in SPSS, with a total of four models, and task performance as our dependent variable. Here, the first model consisted of experience and cognitive ability, personality was introduced in the second model, cognitive styles in the third model, and the interaction term in the fourth model. This allowed us to examine how much incremental validity each of the layers adds over and beyond what was already accounted for, and whether this change was significant.

After the hierarchical regression analysis was conducted, we were able to obtain the regression equation and the covariance matrix for Model 4 (Table 5). We used this information, in addition to their means and standard deviations to plot the simple slope analysis and interpret the interaction. During this whole procedure, we followed both Jeremy Dawson's template for simple slopes (Jeremy Dawson, n.d.), in addition to calculating the regression equations manually. Three levels of intuition and three levels of analysis gave us a total of nine combinations. We calculated all nine coefficient equations for each combination, where "high" and "low" were 1 standard deviation above and below the mean, while "medium" was simply the mean. Further, information from the covariance matrix was used to conduct a simple slope significance test. When we compared our simple slope analysis with that of Bakken (2013), we observed that ours were positioned slightly lower. We found out that this was due to the decision not to mean-center the experience-variable, which ultimately gave us a slightly lower intercept.

4.2 Hypothesis 2a

In explicating the relationship between balanced cognitive styles and task performance in hypothesis 2a, we started by creating a directional difference score (d=ACS-ICS) by subtracting the score on intuitive cognitive style (ICS) from the score on analytic cognitive style (ACS).

The next step was to examine the curve estimations for the relationship between the directional difference score and task performance. These curve estimations include a range of different regression equations, and the analysis is performed in SPSS. The fit of different regression equations are compared. We chose not to include any other variables besides the directional difference score as the independent variable, and task performance as the dependent variable. The rationale was to simply examine whether the best fit was a quadratic regression equation, before we proceeded with a more in-depth analysis with additional variables. As this assumption was supported, we continued with our analysis. We used a Python script (For syntax see Appendix D) to find the maximum value of the regression equation.

4.3 Hypothesis 2b

Similar to hypothesis 1, we conducted a hierarchical regression analysis with four models, where the first three models contain control variables and cognitive styles. Different from the analysis in hypothesis 1, we now introduced the squared directional difference score rather than the interaction term in Model 4 (Table 7). The inclusion of the squared directional difference score, is in order to account for the assumed quadratic relationship between task performance and the directional difference score, supported in hypothesis 2a.

Next, the predictive power of the regression analysis (Model 4, Table 7) was compared to the predictive power of our regression analysis from hypothesis 1 (Model 4, Table 5), containing the interaction term.

5. Results

5.1 Descriptive statistics

Table 3 represents means, standard deviations, skewness and kurtosis. Here, one can see that the mean is 3.73 for analytic cognitive style and 3.35 for intuitive cognitive style. In addition, the skewness statistic is .35 and -.15, for analytic and intuitive cognitive style, respectively. Thus, there are signs of the sample skewing towards a preference for analysis. However, skewed, or asymmetrical distributions are not necessarily uncommon in social sciences (Agresti & Finlay, 2014, p. 38). In addition, as the skewness statistics are not above .5 or below -.5, the skewness can be considered acceptable. Furthermore, it is worth noting that the kurtosis is .41 for analytic and .95, for intuitive cognitive style. Thus, the kurtosis for intuitive cognitive style is quite high and indicates that the distribution has a higher peak than a normal distribution. While .95 is below the threshold at 1 (Hair et al., 2017, p. 61), it is still relatively close and thus worth noting, as it could potentially affect the replicability of our findings due to non-normality (DeCarlo, 1997).

Table 3: *Means, standard deviations, skewness and kurtosis.*

	Mean	Std.	Skewness	Kurtosis
Experience	.31	.46	.84	-1.32
Neuroticism	17.59	6.85	.26	-.09
Extraversion	32.28	5.10	-.10	-.34
Openness	27.10	6.95	.28	-.47
Agreeableness	29.94	5.81	.05	-.53
Conscientiousness	33.65	6.81	-.25	-.43
Intuitive CS	3.35	.52	-.15	-.41
Analytic CS	3.73	.43	-.35	.95
Task Performance	.44	.13	-.24	-.37

N = 107

CS = Cognitive style

5.2 Correlations

Our correlations are depicted in Table 4. To interpret the correlations, we compared them with findings from previous research. It is, however, important to note that these are not intended as direct comparisons, as we cannot expect identical results. The results are likely influenced by different sample sizes, distributions, and measures of constructs. For instance, our measure of task performance is quite specific and narrowed to a simulation of a crisis management setting. Thus, while it might bear resemblance, it will not be directly comparable with other measures of task performance. Neither do we use the same exact measures of personality and cognitive ability as the studies we are comparing to. The purpose was simply to screen for any clear deviations, and some minor variations should be expected.

Table 4: *Correlations.*

	1	2	3	4	5	6	7	8	9
1.Cognitive ability									
2.Experience	.11								
3.Neuroticism	-.14	-.17							
4.Extraversion	.03	.07	-.50***						
5.Openness	.20*	-.32***	.15	.04					
6.Agreeableness	.10	-.17	-.32***	.24*	.02				
7.Conscientiousness	.04	-.36***	-.21*	.27**	.17	.26**			
8. Intuitive CS	-.00	.19	-.16	.29**	-.13	.16	-.01		
9. Analytic CS	.31**	-.20**	-.05	.07	.36***	.04	.48***	-.10	
10.Task Performance	.36***	.40***	-.19	.16	-.19	.05	-.29	-22*	-.14

N = 107

CS = Cognitive style

Significance Levels (all two-tailed): * p <.05; ** p <.01; *** p<.001

Firstly, we looked at the correlations between intuitive and analytic cognitive style and the five personality factors, compared to those reported by Pacini & Epstein (1999). We found that the majority of our correlations were similar with respect to value and direction, with the exception of a few. Pacini & Epstein (1999) reported a correlation of -.38 between analytic cognitive style and neuroticism, .17 between intuitive cognitive style and openness to experiences and .14 between intuitive cognitive style and conscientiousness. However, as Table 4 illustrates, we found a correlation of -.05, -.13 and -.01, respectively. Moreover, with respect to the correlation between cognitive ability and task performance, we find that it is well in accordance with previous research. For instance, we found a correlation of .36 ($p < .001$), and Schmitt (2014) argues that the correlation is usually .40 across different situations. Lastly, the correlation between cognitive ability and analytic cognitive style was .31 ($p < .001$), which is also fairly similar to what Alaybek et al., (2021a) proposed: a significant correlation of .23.

5.3 Hypothesis testing

5.3.1 Hypothesis 1

In hypothesis 1, we examined whether individuals with a medium-medium combination performed as well as individuals with a high-high or low-low combination of cognitive style. The process started by simply conducting a hierarchical regression analysis to obtain the information needed for the simple slope analysis (Table 5).

Table 5: *Hierarchical regression analysis.*

	Model 1	Model 2	Model 3	Model 4
Cognitive ability	.32***	.36**	.38***	.37***
Experience	.37***	.21***	.19*	.23*
Neuroticism		-.03	-.04	-.05
Extraversion		.18	.15	.13
Openness		- .15	-.12	-.13
Agreeableness		.07	.05	.03
Conscientiousness		-.28**	-.24*	-.21*
Intuitive CS			.11	.08
Analytic CS			-.06	-.03
Interaction				.24**
Adjusted R^2	.25	.32	.31	.37
F change	18.58***	2.99*	.99	8.75**

N = 107

Table represents standardized regression coefficients

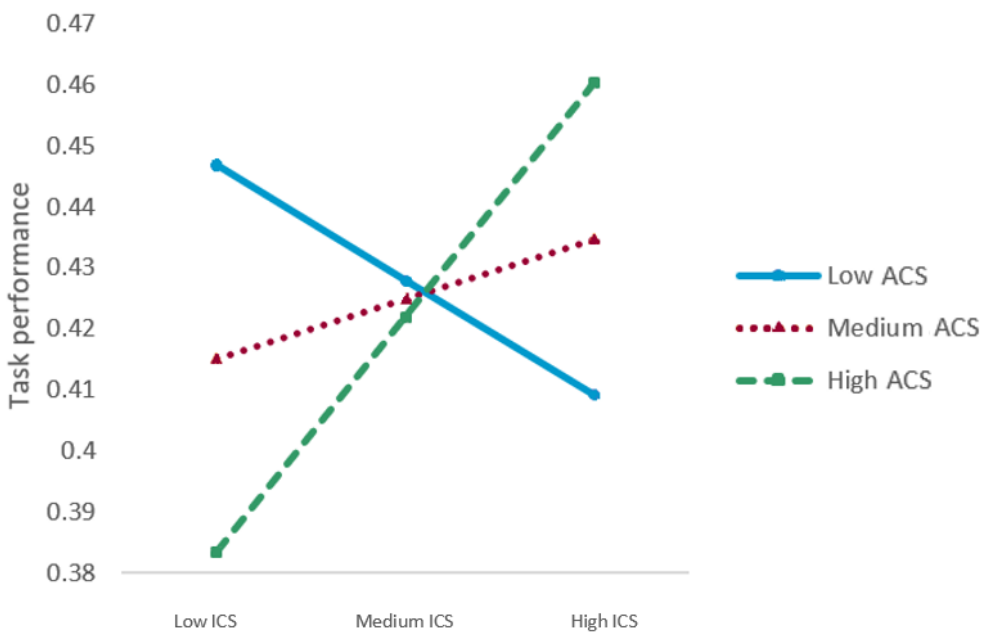
CS = Cognitive style

Significance Levels (all two-tailed): * p <.05; ** p <.01; *** p<.001

In Table 5, we can see that Model 1 consists of cognitive ability and experience. Both variables are significant ($p < .001$), and they collectively explain 25% of the variance in task performance. In Model 2, we introduced the five personality factors, in which conscientiousness was the only significant predictor (standardized $\beta = -.28$, $p < .01$). This is not particularly unexpected. As previously mentioned, conscientiousness has been shown to be the most valid or robust predictor across contexts, whilst the remaining Big Five personality traits seems to vary depending on the context (e.g., Barrick & Mount, 1991; Schmidt & Hunter, 1998). What is unexpected, however, is that conscientiousness has a significantly *negative* effect on task performance, which contradicts previous findings. Nevertheless, by adding the five personality factors, our model now explains 32%

of the variance in task performance, and has had a significant increase from the previous model ($p < .05$). In Model 3, we introduce intuitive and analytic cognitive styles, in which none of them have a significant main effect. Consequently, by including them, the model has not obtained a statistically significant change compared to the previous model. In Model 4 however, we can see that their interaction term is in fact significant ($p < .01$), and our model now explains 37% of the variance in task performance, which is a significant increase from the previous model. Thus, as discussed by Bakken et al. (n.d.); although the main effects of intuitive and analytic cognitive styles are nonsignificant, by accounting for their interaction, we add incremental validity over and beyond cognitive ability, experience, and personality, and consequently increase our ability to predict variance in task performance.

Figure 3: *Simple slope analysis.*



N=107

Based on Model 4, Table 5

ICS = Intuitive cognitive style. ACS = Analytic cognitive style

Low = 1STD below the mean. Medium = the mean. High = 1STD above the mean

Gradients of the slopes: Low ACS = -.036; Medium ACS = .019; High ACS = .074*

Significance Levels: * p <.05; ** p <.01; *** p <0.001

Lastly, in Figure 3, we have conducted a simple slope analysis based on the regression equation obtained from Model 4 in Table 5. The figure shows three slopes, depicting the categories of low, medium, and high analysis. These intercept the points of low, medium and high intuition. As depicted in Figure 3, we can see that the medium-medium combination seems to perform better than the dominant high-low and low-high combinations. In fact, all the combinations including medium analysis seem to perform better than the high-low and low-high combinations. However, medium-medium does not seem to perform as well as their other balanced counterparts; high-high and low-low. On the other hand, it is important to note that, similar to Bakken et al. (2013), our low analysis slope was not significant (slope gradient = .074, n.s.), and neither was our additional medium analysis slope (slope gradient = .019, n.s.). Thus, although we did not find any support for hypothesis 1, nor did we find firm evidence against it.

5.3.2 Hypothesis 2a

The analysis of hypothesis 2a started with the comparisons of different curve estimations. The analysis included linear, quadratic, cubic, exponential and logistic regressions. While we hypothesized the best fit to be the quadratic regression, we sought to compare a wide range of different regression equations in order to properly assess whether the quadratic regression equation was the best fit, or if there was a better alternative. Here, the dependent variable was task performance, and the independent variable was the directional difference score. No other variables were included in this analysis. The results of the regression analysis are shown in Table 6.

As predicted, the best fit was a quadratic regression equation, with 9% explained variance in task performance, which is significant at the .01 level. While the cubic regression is close, at 8%, the significance-level is lower than for the quadratic. In addition, the quadratic regression equation is preferable due to the principle of parsimony. Thus, it is reasonable to conclude that the quadratic curvilinear regression equation is the best fit between directional difference score and task performance, for our sample.

Table 6: *Curve estimation: directional difference score and task performance*

	R^2	Adjusted R^2	Sum of squares Regression	Sum of squares Residual	Sig.
Linear	.06	.05	.10	1.55	.010*
Quadratic	.10	.09	.17	1.49	.004**
Cubic	.10	.08	.17	1.49	.010*
Exponential	.07	.06	.79	10.95	.007**
Logistic	.07	.06	.79	10.95	.007**

N = 107

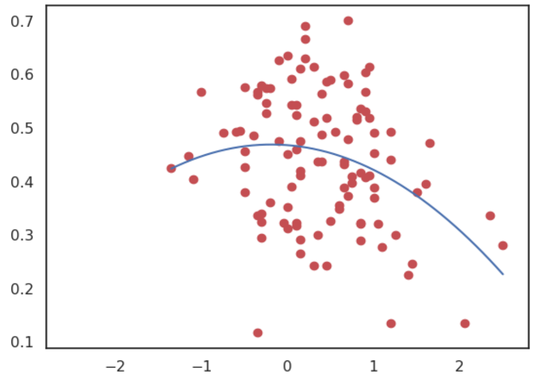
Significance Levels (all two-tailed): * p <.05; ** p <.01; *** p <0.001

Predictor: Directional difference score

Dependent variable: Task performance

The scatterplot with the best fit is illustrated in Figure 4. As can be seen in the model, the estimated best fit is specifically a negative quadratic regression equation. Thus, the results support the initial part of our hypothesis: the relationship between cognitive balance and task performance in crisis management follows the slope of a negative quadratic regression equation.

Figure 4: *Curve estimation: Directional difference score and task performance.*



N = 107

Predictor: Directional difference score

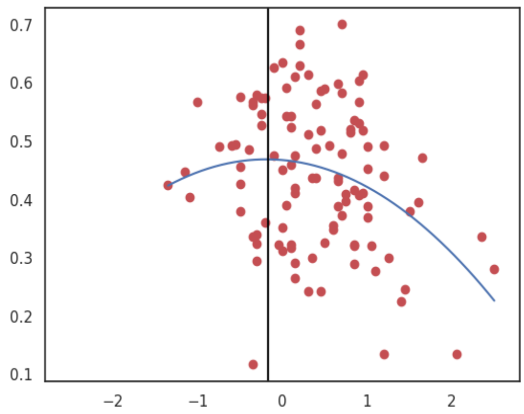
Dependent variable: Task performance

Note: The directional difference score ranges from -5 to 5. Due to the participants' responses ranging from -1.35 to 2.5, the x-axis only depicts -3 to 3

It is worth noting that while the range of the directional difference score spans from -5 to 5, our sample has the minimum score of -1.35 and a maximum of 2.5. Thus, the curve is only estimated for this area.

Next, we examined the maximum value of the quadratic regression equation in order to assess which directional difference score predicts the best task performance. This is depicted in Figure 5, where the vertical line represents the maximum value of the regression equation. As can be seen in the figure, the maximum value is quite close to zero. Specifically, the maximum value of the regression equation is at d= -.17. In other words, the regression equation predicts ideal task performance when a person has a balanced approach with a very slight preference for intuition. While -.17 is not zero, we argue that this is close enough to constitute support for our hypothesis. Thus, we conclude that the results support the latter part of hypothesis 2a; the maximum value of the regression equation is at approximately d=0.

Figure 5: *Directional difference score and task performance with maximum value.*



N = 107

Predictor: Directional difference score

Dependent variable: Task performance

Vertical line depicts maximum value: d = -.17

Note: The directional difference score ranges from -5 to 5. Due to the participants' responses ranging from -1.35 to 2.5, the x-axis only depicts -3 to 3

5.3.3 Hypothesis 2b

We next performed a hierarchical regression analysis, which included the control variables of personality, cognitive ability and experience, in addition to the main effects of intuitive and analytic cognitive style and the squared directional difference score. The results of this analysis are represented in Table 7, Model 4, which introduces the squared directional difference score is estimated to explain 35% of the variance in task performance. Furthermore, it has an F change at 6.69, significant at the .05 level. It is further worth noting that the introduction of the squared directional difference score increases the explained variance in task performance by 4%. In addition, the variable's significance level shows that it has incremental validity over and beyond experience, personality, cognitive ability and intuitive and analytic cognitive style.

Table 7: *Hierarchical regression analysis.*

	Model 1	Model 2	Model 3	Model 4
Cognitive ability	.32***	.36**	.38***	.38***
Experience	.37***	.21***	.19*	.19*
Neuroticism		-.03	-.04	-.04
Extraversion		.18	.15	.15
Openness		- .15	-.12	-.14
Agreeableness		.07	.05	.02
Conscientiousness		-.28**	-.24*	-.24*
ICS			.11	-.03
ACS			-.06	.04
Difference sq				-.27*
Adjusted R^2	.25	.32	.31	.35
F change	18.58***	2.99*	.985	6.69*

N = 107

Table represents standardized regression coefficients

Significance Levels (all two-tailed): * p <.05; ** p <.01; *** p<.001

Difference sq = Squared directional difference score

These results were then compared to the hierarchical regression we performed in hypothesis 1, where the interaction term replaced the squared directional difference score in Model 4. These results are represented in Table 5, in hypothesis 1. As discussed in hypothesis 1, Model 4 was estimated to explain 37% of the variance in task performance. Comparing the two proposed models, the difference model and the interaction model, the latter has slightly greater predictive power than the former. While these results contradict hypothesis 2b, it is worth noting the similarity in explained variance. As the two models are so similar in explained variance, the findings may be due to other statistical reasons, like the specific sample. As such, we cannot conclude that the interaction model is preferable with certainty.

6. Discussion

In this section, we will first discuss the key findings of our hypotheses in regards to the research question, as well as the value and contribution of our findings. Next, limitations regarding sample and methodology are considered. The section is concluded by a discussion regarding potential future research.

6.1 Hypothesis 1

Above, we have presented the results of the analyses. With respect to hypothesis 1, our simple slope analysis indicated that the balanced medium-medium combination had a higher task performance than the dominant high-low and low-high combinations. Still, they did not seem to perform as well as the other balanced combinations, high-high and low-low. However, as the low and medium analysis slopes were not significant, we are not able to draw any firm conclusions regarding the favorability of the different combinations in comparison to each other. Nonetheless, we find this discussion to be an important one, based on two notions.

Firstly, Bakken et al. (n.d.) did not find the high analysis slope to be significant in their study on individuals. However, they did find it significant in their study on teams. Thus, there is at least some evidence that the slopes can be significant under other circumstances, whether this is due to the different sample or unit of analysis. If this is the case, a more nuanced discussion is highly appropriate. Secondly, although there seems to be a general tendency within the field to regard balance as advantageous, few have been specific as to what balance precisely entails. As part of our rationale for hypothesis 1, we wanted to examine whether a medium-medium combination followed the principles of balance, or rather revealed contingencies.

If there is any significance to the high-high and low-low combinations performing substantially better than the medium-medium combination, then it might seem like contingencies do exist. The results would indicate that balance is advantageous *when* it is balanced at the end points: either high or low on both cognitive styles. Contrary, when the individual has a moderately balanced cognitive style, they do not perform equally well. The proposed main mechanism, cognitive flexibility, would not suffice to explain this observation. As previously mentioned, from this stance, one would assume that a medium-medium combination would be as cognitively flexible as the high-high and low-low combinations. The same is true for the other main mechanisms proposed, as they all build on the assumption of balance as advantageous. Thus, a next and perhaps more difficult question is, what are the theoretical explanations for a lower performance of the medium-medium combination?

As the theoretical literature on cognitive styles does not provide any clear explanation, we turn to the literature on motivation. We argue that one possible explanation may lie in individuals' *motivation* to switch between cognitive styles. In its most basic form, motivation has been assumed to drive us towards something, and away from others. Gray (1991, as cited in Holt et al., 2012, p. 402) suggested that these two universal tendencies reflect the activity of two neural systems in the brain: the behavioral activation system and the behavioral inhibition system. We suggest that the same mechanism can be used to explain the possibility for a medium-medium combination to deviate from the principles of balance. Firstly, individuals who score a low preference on both styles can be argued to have an equal aversion to both styles. This means that the individual may switch from one to the other when necessary, simply because they dislike the style they are currently using. Conversely, those who score a high preference on both styles might switch from one to the other because they are enthusiastic or drawn to use the other. In other words, both combinations entail some sort of motivation to either avoid or approach, which might ultimately motivate one to switch more easily. On the other hand, individuals with an average preference for both styles might be more indifferent to a switch, as they are neither motivated by approach nor avoidance. Consequently, their cognitive flexibility could be impaired by their motivation, rather than ability to switch, which in turn might influence their task performance.

Alternatively, a deviation from the medium-medium combination might have a purely statistical explanation, due to the way the scores are obtained. Self-reported measures on a Likert scale, such as REI-40, are susceptible to a common and well-established bias within the field of psychology, namely the central tendency bias. This bias refers to a tendency in which individuals avoid the end points of a response scale, and prefer responses in the middle (Douven, 2018). We suggest that this bias might explain the statistically lower task performance of the medium-medium combination.

One can argue that an individual with a combination including a medium level of cognitive style, such as high-medium or low-medium, is likely able to produce answers unaffected by the central tendency bias. As they were able to score high or low on one construct, their scores might be more indicative of their true score, rather than a bias. An individual who scored medium-medium, on the other hand, might be more likely affected by the bias, as they score medium on both constructs. If this is true, one can argue that there might be individuals within the medium-medium combination whose real cognitive style might differ from their obtained REI-40 scores. More specifically, as they yield lower task performance, one can theorize that their cognitive style is in actuality unbalanced. This is, however, difficult to assess properly, as some individuals will, inevitably, have an unbiased medium-medium score.

6.2 Hypothesis 2a

In the results for hypothesis 2a, we found support for the balance theory, through the discovery of a negative quadratic relationship between the directional difference score and task performance. This indicates that those with a balanced cognitive style perform better than those with a predominantly intuitive or analytic cognitive style. Furthermore, the maximum value of the regression equation was approximately at $d = 0$, which predicted the best task performance in our sample. Thus, the results of our attempt to more accurately examine what balance entails, suggest that the most optimal balance is a near perfect balance, rather than a more skewed one, as proposed by Mohaghegh and Größler (2020). Thus, collectively, these results support the idea that balance between intuitive and analytic cognitive style explains variation in a simulated crisis management setting. Furthermore, the results might also have implications for dual-process and unimodel perspectives of cognitive style.

As stated, Bakken et al. (n.d.) found that the interaction term of intuitive and analytic cognitive style was a significant predictor of task performance. This finding is in accordance with the dual-process perspective, where analytic and intuitive cognitive styles are assumed to be independent constructs, yet operating in a parallel and interactive manner (Pacini & Epstein, 1999; Stanovich & West, 2000). Bakken et al. (n.d.) also found that balance may be important, as high-high and low-low combinations performed the best. Thus, we wanted to examine this theory of balance further.

We quantified balance through the directional difference score in order to study the impact of balance on task performance. The directional difference score is a scale, from complete intuitive cognitive style at one end (-5), to complete analytic cognitive style at the other (5). In the middle, we find the perfect balance between the two styles at 0. However, this methodology is to a certain extent flawed, as it ends up contradicting our original theoretical positioning of the dual-process perspective. Subtracting intuitive cognitive style from analytic cognitive style to obtain a directional difference score is, from a dual-process perspective, incorrect, as they are considered two independent constructs. As such, subtracting one from the other makes as much sense as subtracting oranges from apples. Furthermore, the directional difference score resembles a continuum ranging from highly intuitive to highly rational, as proposed by unimodel perspectives. (e.g., Keren & Schul, 2009; Kruglanski & Gigerenzer, 2011; Osman, 2004). For this reason, one can argue that hypothesis 2a and 2b take on a unimodel perspective of cognitive style, rather than the dual-process perspective.

The reason for this is simply that we found no other way to quantify balance without ending up with a unimodel perspective. The alternative to a directional difference score is an absolute difference score, which we also contemplated using. However, we would face the same issues with the absolute score, as it would still involve subtracting intuition from analysis, consequently contradicting the assumption of independence. Consequently, one can argue that the exploration of balance between cognitive styles, at least in the way we have quantified balance, might be a unimodel perspective subject. Furthermore, one might even argue that the potential importance of balance may be an argument in favor of the unimodel perspective in general. If balance is the most important predictor for task performance, perhaps the two styles are better suited as opposites on the same continuum, and, consequently, as the same construct. Conversely, the exploration of the interaction term takes a dual-process perspective, and the earlier findings of the interaction term being a significant predictor of task performance, is supportive of the dual-process perspective. Thus, in our exploration, we have found that a more nuanced discussion regarding the impact of balance requires an equally nuanced examination of one's theoretical position.

6.3 Hypothesis 2b

In the results for hypothesis 2b, we found that the difference model, containing the squared directional difference score explained 35% of the variance in task performance. Furthermore, the squared directional difference score was a significant predictor of task performance. These findings are all in support of the balance theory. As we have not found any previous studies where balance between intuitive and analytic cognitive style has been quantified and tested, the results of our analysis might provide a novel contribution. In addition, as our dependent variable was task performance in a simulated crisis management setting, we might be one step closer to understanding the potential impact of balance between cognitive styles in crisis management.

On the other hand, the interaction model, containing the interaction term, explained 37%. Thus, the two models are very close, with the interaction model explaining merely 2% more of the variance in task performance than the difference model does. In other words, we cannot conclude with certainty that the interaction model is superior to the difference model. The difference in explained variance is so small, that one cannot rule out that another sample might produce findings where the difference model explains more.

The interaction model does, however, have some strengths the difference model lacks. Firstly, multiplicative interaction terms are widely used within social sciences (Hainmueller et al., 2019), and in the field of cognitive style specifically (e.g., Bakken et al., n.d.; Mahoney et al., 2011). In addition, the interaction model takes on the dual-process perspective, which is arguably the most established perspective, with the most empirical support (e.g., Epstein et al., 1996; Norris & Epstein, 2011; Wang et al., 2017; Lieberman, 2003; Evans, 2008). Conversely, we have not found any literature on cognitive style where a directional difference score has been used. As previously mentioned, the variable can also be easily criticized from the dual-process perspective for subtracting one independent construct from another, consequently creating a unimodel scale with one cognitive style at each end. We have, however, deliberated whether a dual-process perspective on cognitive processing is directly translatable to a dual-process perspective on cognitive style. That being said, there exists meta-analytic evidence for the orthogonal nature of analytic and intuitive cognitive style as well (Wang et al., 2017; Phillips et al., 2016; Alaybek et al., 2021b). As such, the criticisms of a unimodel perspective are equally relevant in the discussion of cognitive style as in cognitive processing.

When further interpreting the findings, there may be a reason for why the difference model may not perform as well as the interaction term, which lies in the results of hypothesis 1. While not significant, our simple slope analysis indicates that the medium-medium combination may perform somewhat poorer than the low-low and high-high combinations. If this is true, the medium-medium combination might decrease the predictive power of the difference model by lowering the overall performance of the group scoring around zero on the directional difference score. The problem is that there are few, if any, ways to assess this assumption, without cherry picking data, potentially causing biased results (Murphy & Aguinis, 2019). It would, nevertheless, be interesting to understand how the interaction model might be affected by the medium-medium combination, and how that compares to the difference model.

A last, notable aspect of our findings, relates to our control variables. While experience, cognitive ability and personality are frequently emphasized as predictors of performance, especially in selection (Schmidt & Hunter, 1989), cognitive style has received less attention. However, these findings indicate the predictive and incremental validity of cognitive style over and beyond experience, personality, and cognitive ability. This is true of both the squared directional difference score and the interaction term, as shown in both our analysis and the analyses of Bakken et al. (n.d.). This sheds light on the potentially undervalued importance cognitive style might have, for example in selection of individuals working in crisis management-related fields. As such, there is arguably a need for increased attention on cognitive styles in the field of organizational psychology.

6.4 Implications

Our findings have several implications, both practical and theoretical. Firstly, we found indications that the medium-medium combination might not perform as well as the high-high and low-low combinations. If there is any significance to this finding, it would shed light on the theoretical literature, or the lack of theoretical literature, pertaining to balance between cognitive styles. More specifically, it would indicate that contingencies exist, and nuances must be accounted for, as the effect of balance between cognitive styles would seem to depend on its level. To explain this possible observation, we have turned to the literature on motivation, by suggesting that the motivation to cognitively switch might be as important as the ability to cognitively switch.

More evidently, however, are the theoretical implications of our quantification of balance. In an attempt to quantify balance, we recognized a potentially unavoidable shift from a dual-process perspective to a more unimodel one. Although scholars within the dual-process perspective have for some time discussed the advantage of balance between cognitive styles (e.g., Louis & Sutton, 1991; Epstein, 1994; Hodgkinson & Clarke, 2007), it seems as an empirical quantification of balance is challenging without a unimodel perspective. As previously mentioned, Keren and Schul (2009) critiqued the dual-process perspective for a lack of theoretical coherence, which in turn makes it difficult to obtain empirical support for the assumptions made. Along the same line, these findings raise awareness for a lack of clear norms regarding how to quantify and empirically measure balance in a way that is in alignment with the dual-process perspective.

Lastly, there are practical implications regarding the predictive and incremental validity of the directional difference score. While experience, cognitive ability and personality are measures frequently used for recruitment and selection purposes (Schmidt & Hunter, 1989), we found the squared directional difference score to have incremental validity over and beyond these measures. Thus, these findings highlight the usefulness of measuring balance between cognitive styles when predicting task performance, particularly for individuals who must bear responsibilities in crisis management settings, or VUCA environments in general.

Further, just as with personality and cognitive ability, longitudinal studies have shown that cognitive style is a relatively stable and enduring predisposition (Clapp, 1993). Thus, any training interventions aimed at changing cognitive style are likely to fail (Clapp, 1993). Individuals might alter their behavior if their cognitive style does not match the task, however, working outside one's preference reflects a "coping behavior" (Clapp, 1993). Over an extended period, this would be costly for the individual who must deploy more energy, and consequently ineffective for the organization (Isaksen, 2013). As our findings indicate that a balanced cognitive style is preferred over a dominant cognitive style in a crisis management setting, practitioners can rather lever these differences and achieve “coverage” by assessing individuals’ cognitive style and match the people with the task (Isaksen, 2013). Ultimately, this would reduce coping for the individual, and maximize productivity for the organization.

6.5 Limitations

6.5.1 Sample limitations

Heterogenous sample: Our first, and perhaps most obvious, limitation revolves around the composition of the sample in our data. We have used data collected at MindLab at BI Norwegian Business School. Thus, our sample exclusively consists of students at BI and external students at the Norwegian Military Academy. Further, the sample has a mean and median age of 23.7 and 22, respectively. Consequently, generalization might be limited due to the low variance in age and occupation among participants. Thus, it is important to point out the limitations in regards to representability of the general population, as one can theorize that factors such as age and work experience might impact the results. The fact that our sample consists of relatively young participants with active student status, may also mean that our findings might not be representative of managers and leaders working with real crisis management situations. Perhaps more experienced crisis managers regard the cognitive styles differently than younger and less experienced individuals.

Another sample limitation lies in participants’ gender. Only 29.9% of participants are female. This is in of itself a limitation, as women are underrepresented in our sample. Furthermore, it is worth noting that all women except one in the sample were BI students. Thus, there is only one female participant from the Norwegian Military Academy (See Apendix A for further sample details). The lack of female participants with military experience can clearly be considered a limitation, due to a potential impact of gender and military experience on performance.

Sample skewness: While we have previously noted the skewness statistic, there is another skewness worth noting as well. Namely, the fact that 75 (70.1%) have a preference for analysis. In addition, there are no participants with a strong preference for intuition (Figure 4). Due to this skewness in regards to cognitive style, and lack of participants with a strong preference for intuition, we might be lacking the full picture in understanding the preference for intuition, and its influence on task performance.

Data reuse: The data received has previously been used by Bakken (2013) and Bakken et al. (n.d.). As we are using this dataset for a separate project, it constitutes reuse of data according to Pasquetto et al (2017). There is, however, little known about the potential issues related to data reuse. One can theorize that reuse might lead to a higher chance for type 1 errors to occur, but this is purely speculation (Pasquetto et al., 2017). Further, we argue that our hypotheses are different enough from the hypothesis of Bakken et al. (n.d.), to allow this re-use of data. We are also in close contact with one of the researchers who have collected the data, Thorvald Hærem, as he is our supervisor. This can lower chances of any misunderstandings regarding the data. Lastly, there is a point to be made about the way these data have been gathered. MindLab is in use by several PhD candidates, and as such the data is intended to be built upon over the years. When this is the case, the data may be more usable by people other than the original data gatherer(s) (Pasquetto et al., 2017; Goodman et al., 2014).

6.5.2 Methodological limitations

Same Source Bias: Our first methodological limitation is that both independent and dependent variables are collected from the same participants. While this is not uncommon, it can lead to same source bias. Podsakoff et al. (2012) found that same source data could lead to much larger effects than data collected from different sources. Thus, the size of our findings might be impacted by the same source data material. The material is also gathered at the same time, meaning that there is no temporal separation, which has the potential of counteracting same source bias (Podsakoff et al., 2012).

Simple slope analysis: Another limitation pertains to the use of simple slope analysis and the limited information they provide under certain circumstances. As we sought to examine the relationship between intuitive cognitive style and task performance at specific levels of analytic cognitive style, one could argue that the use of simple slope analysis was appropriate (Dawson, 2014). However, our findings still bear the limitation that we have used relatively arbitrary levels: the mean, and one standard deviation below and above the mean. As we did not find any more meaningful values within the literature, it is important to emphasize that these levels are not theoretically grounded, and thus bear little intrinsic meaning (Dawson, 2014).

Crisis management context: The task performance measure is specifically conducted in a simulated crisis management setting in the form of a digital microworld. Thus, differences in familiarity with or preference for video games might impact one's ability to perform. Further, performance is measured by simulations, not real crisis management situations. While this does come with a high degree of control, there are also some limitations in regard to the validity of simulated tasks. In real crises one can expect people to have a much higher emotional activation than when sitting in front of a computer, knowing that one's performance will not have real consequences. Thus, it is difficult to say whether cognitive styles might impact performance and behavior differently in a real-life crisis setting than in a simulated one.

Social desirability: Another aspect to consider is the potentially biased self-report measures. Social desirability can be defined as "the tendency to distance oneself from socially unacceptable behavior or to try to show oneself in a good light" (Cooper, 2015, p. 323). A self-report personality test like the NEO-FFI is especially prone to social desirability, due to how easy it is to consciously or unconsciously produce untrue or biased answers (Birkeland et al., 2006). The same can be true for the REI-40 measures of cognitive style. Theorists have historically tended to view intuition as less favorable and more prone to errors, as compared to the "legitimate contributor" of analytic reasoning (e.g., Tversky & Kahneman, 1974; Kahneman & Frederick, 2002; Sayegh et al., 2004; Evans, 2010;). It is possible that some respondents might have similar views, which can influence participants' reported preference for intuition and analysis on the REI-40. In fact, the vast majority of our participants (70.1%) did prefer analysis over intuition, which *might* potentially indicate the possibility of social desirability playing a role.

The directional difference score: The last methodological limitation pertains to the directional difference score being derived from the REI-40 measurement. The REI-40 is based on a dual-process perspective, while the directional difference score is more in line with the unimodel perspective. Thus, it may be more suitable to utilize a more compatible measure of cognitive style.

6.6 Future research

While our thesis has answered many of our questions, it has also shed light on important topics for future research. One of the most important may be regarding the medium-medium combination. Despite the insignificance of two slopes in the simple slope analysis, our findings indicate that the medium-medium combination do not perform as well as the high-high and low-low combinations. We have suggested that this may be due to the motivation, rather than ability, to cognitively switch. It would therefore be interesting for further research to firstly examine whether this observation significantly replicates, and secondly, what the theoretical reasoning behind it may be.

Furthermore, it would be interesting for future research to attempt to replicate our findings on a larger sample. This is for two reasons: Our sample is somewhat small, and the difference model and the interaction model were extremely close to explaining the same amount of variance in task performance, with the interaction model explaining merely 2% more. Thus, we have not been able to firmly conclude whether one model is better than the other. If the same research is performed at a larger scale, one might potentially find different results or more evident differences than we have been able to in this thesis.

Another potential direction for future research could be to perform a similar analysis, where a unimodel measurement of cognitive style is utilized instead of the dual-process REI-40. As the directional difference score follows the principles of the unimodel approach, it might be more in line with the theoretical perspective to assess cognitive style with a unimodel measurement. It is, however, worth noting that these measurements are likely to produce different variables than the two variables from REI-40. Consequently, the quantification of balance may be different than the directional difference model created in this thesis.

A last topic for future research pertains to the context of task performance. In this thesis, the measure of task performance was gathered in a simulated crisis management setting. Phillips et al. (2016) and Calabretta et al. (2017), emphasize the potential importance of compatibility between cognitive style and task requirements. While intuition might be preferable for some tasks, analysis might be ideal for other tasks. Thus, our findings can only be transferable to simulated, and potentially real, crisis management settings. However, the use and preference for intuition and analysis may affect other situations differently or similarly to the setting of crisis management. For this reason, it would be interesting to further understand how balance between cognitive styles may affect task performance in other settings.

7. Conclusion

In this thesis we aimed to further study the fairly new balance theory, suggesting that balance between cognitive styles, regardless of the styles per se, yields better task performance than a dominant style in a simulated crisis management setting (Bakken et al., n.d.). Specifically, we asked: to what extent does balance between cognitive styles explain variation in task performance in a simulated crisis management setting?

In hypothesis 1 we introduced a medium slope in our simple slope analysis. While the low and medium slopes were not significant, the findings indicate that the medium-medium combination of cognitive style does not perform as well as the high-high and low-low combination. We have theorized that this may be explained through theories of motivation, or potentially the central tendency bias. If these findings are valid, they challenge the idea that balance between cognitive styles might explain task performance, and as such indicate that contingencies might exist.

In hypothesis 2a we found the relationship between the directional difference score and task performance to be a negative quadratic regression equation. This supports the theorized role of balance between cognitive styles in explaining task performance in a simulated crisis management setting, as it is assumed that a balanced cognitive style is more advantageous than a predominantly analytic or intuitive cognitive style. Furthermore, the ideal balance for task performance seems to be a near perfect balance between intuitive and analytic cognitive style. However, in our attempt to quantify balance, we recognized a shift from our original dual-process position, to a more unimodel one. Thus, one can argue that the subject of balance between cognitive styles might potentially be more in line with the unimodel perspective, or alternatively that the dual-process perspective could benefit from clearer norms for hypothesis testing, as critics have argued (Keren & Schul, 2009).

In our last hypothesis, 2b, we found support for the explanatory power of balance between cognitive styles on task performance, in that the difference model explained 35% of the variance in task performance, and the squared directional difference score was a significant predictor of task performance. However, the interaction model was slightly preferable, with 2% more explained variance. It is also worth noting, however, that the explanatory power of the difference model might be negatively affected by the medium-medium combination. We also found that the interaction term explained 5% of task performance, over and beyond measures of cognitive ability, personality, and experience, while the squared directional difference score added 4% of the explained variance. Thus, one can argue that almost all the variance explained by the interaction term is in fact explained by balance between cognitive styles. In addition, the incremental validity of both of the models over and beyond measures of experience, personality and cognitive ability, emphasizes the practical value of cognitive style for selection purposes.

In conclusion, we found evidence for the explanatory and incremental power of balance between cognitive styles on task performance in a simulated crisis management. While our findings improved our understanding of balance between cognitive styles, it also highlighted topics for future research, particularly with respect to the medium-medium combination and the dual-process versus unimodel perspective. Thus, we argue that, in order to take a step forward, we need to take two steps back and reassess the basics. Nonetheless, this might be a step in the direction of better understanding how we can prepare for the crises of tomorrow.

8. References

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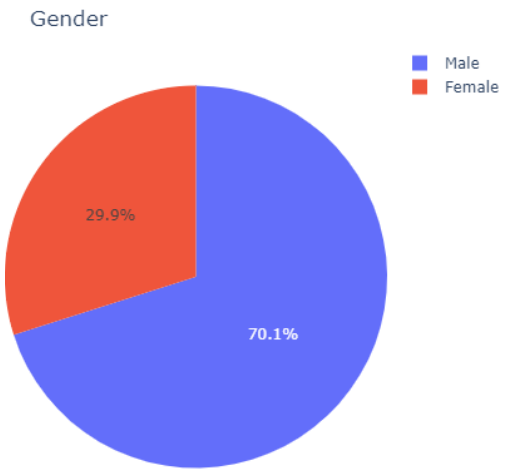
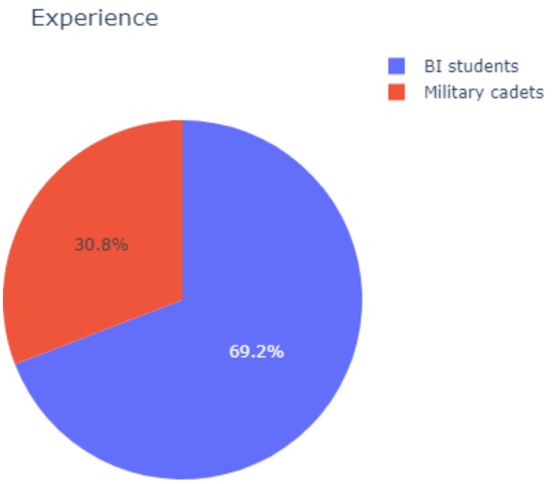
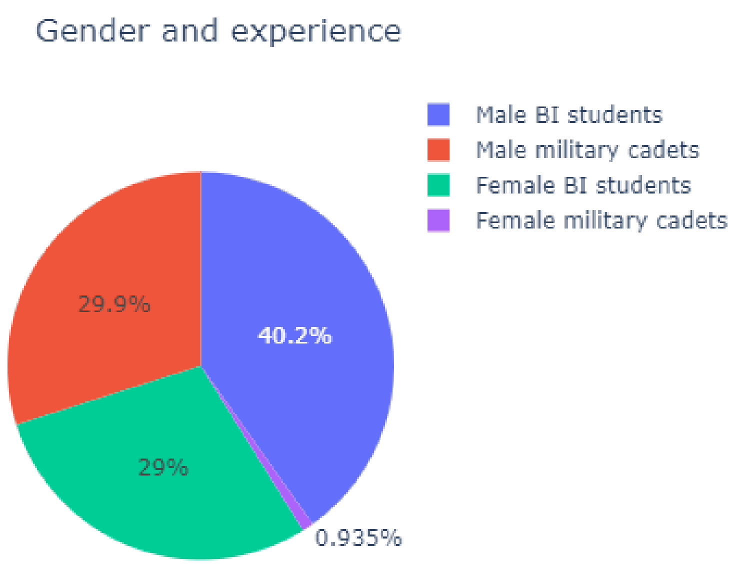
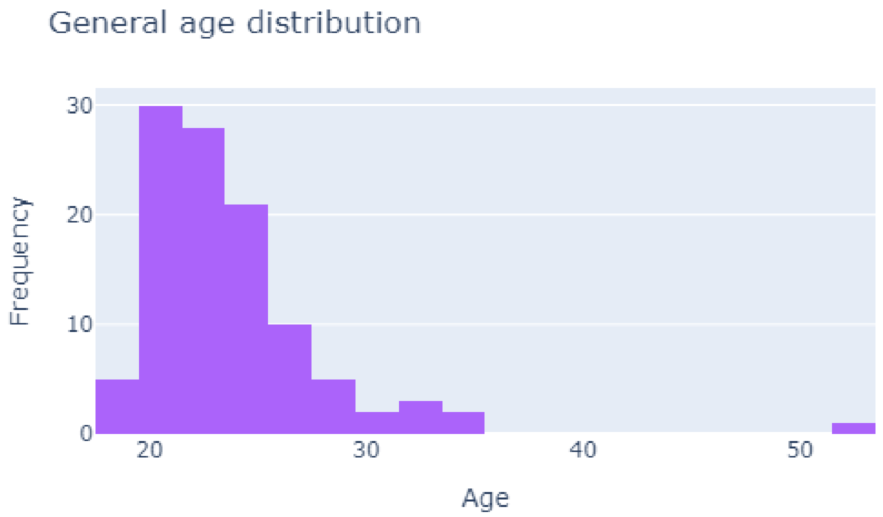
9. Appendices

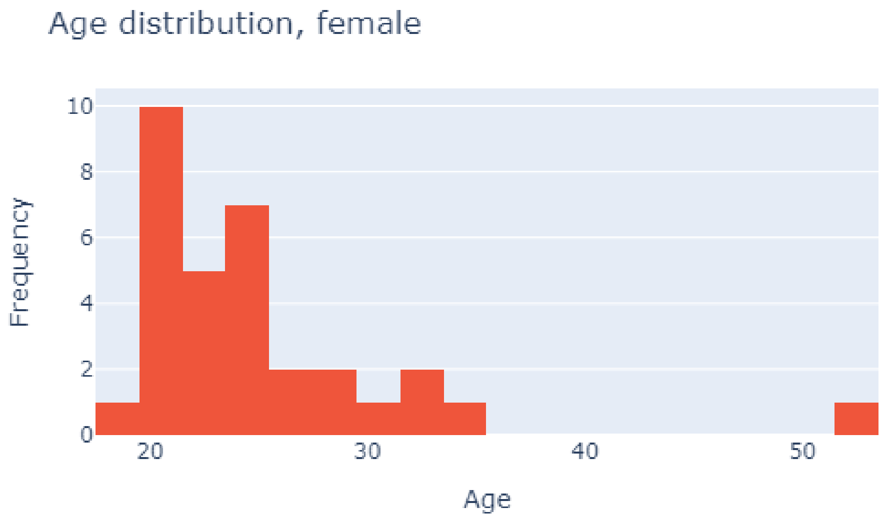
Appendix A: *Sample composition*

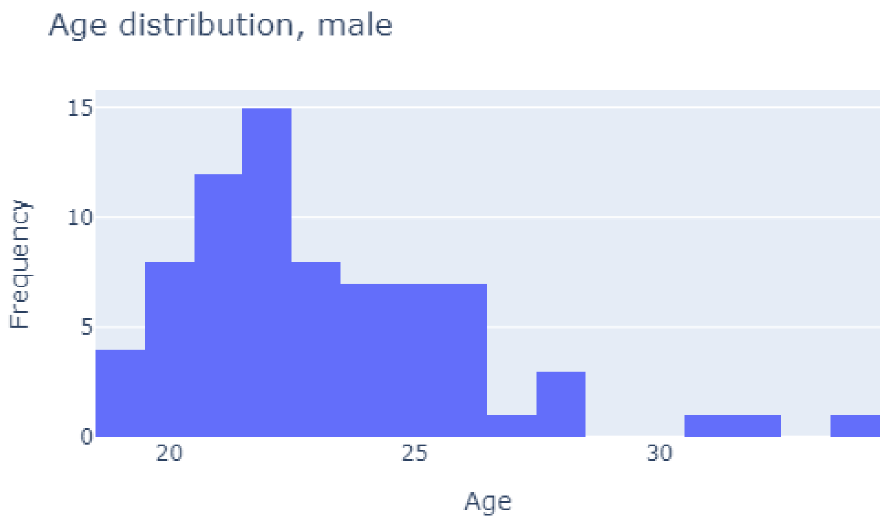







General age distribution
Frequency
30
20
10
0
20
30
40
50
Age


Age distribution, female
Frequency
10
8
6
4
2
0
20
30
40
50
Age


Age distribution, male
Frequency
15
10
5
0
20
25
30
Age

Appendix B: *Tests of linearity*

Table: *Hierarchical regression analyses*

Intuitive cognitive style

Model	Adj. R^2	R^2 change	F change	Sig. change
1. ICS	.04	.05	5.40	.022*
2. ICS sq	.03	.00	.043	.836

Analytic cognitive style

Model	Adj. R^2	R^2 change	F change	Sig. change
1. ACS	.01	.02	2.11	.150
2. ACS sq	.04	.04	3.89	.051

Interaction term

Model	Adj. R^2	R^2 change	F change	Sig. change
1. Interaction	.01	.02	1.67	.199
2. Interaction sq	.01	.02	1.69	.196

N = 107

Significance Levels (all two-tailed): * p <.05; ** p <.01; *** p <0.001

ICS = Intuitive Cognitive style, ACS = Analytic Cognitive style

Sq: Squared

Dependent variable: Task performance

Table: *Curve estimations*

Intuitive cognitive style

			Sum of squares		
	R^2	Adjusted R^2	Regression	Residual	Sig.
Linear	.05	.04	.08	1.58	.022*
Quadratic	.05	.03	.08	1.58	.072

Analytic cognitive style

			Sum of squares		
	R^2	Adjusted R^2	Regression	Residual	Sig.
Linear	.02	.01	.03	1.6	.150
Quadratic	.06	.04	.08	1.6	.053

Interaction term

			Sum of squares		
	R^2	Adjusted R^2	Regression	Residual	Sig.
Linear	.02	.01	.12	1.5	.006**
Quadratic	.03	.01	.12	1.5	.022*

N = 107

Significance Levels (all two-tailed): * p <.05; ** p <.01; *** p <0.001

Dependent variable: Task performance

Appendix C: *VIF*

Table: *VIF scores, uncentered and centered variables*

	Uncentered variables	Centered Variables
Cognitive ability		1.23
Experience	1.47	1.47
Neuroticism	1.58	1.58
Extraversion	1.54	1.54
Openness	1.34	1.34
Agreeableness	1.26	1.26
Conscientiousness	1.72	1.72
Intuitive CS	80.60	1.18
Analytic CS	41.60	1.65
Interaction	109.54	1.09

CS = Cognitive style

Appendix D: *Python script*

Python script used to find the maximum value of the regression equation:

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sb
import numpy as np

data = pd.read_excel("data.xlsx") #Read excel file
x = data['Directional difference score'].tolist() # Retrieve data from columns with name"
y = data['Task performance'].tolist()
coefficients  = np.polyfit(x,y,2)
poly = np.poly1d(coefficients)

new_x = np.linspace(min(x), max(x)) # Array of x values to plot polyfit
new_y = poly(new_x)
max_y = max(new_y)
index_max_y = np.where(new_y == max_y)
max_xy_value = new_x[index_max_y]

print("X axis value where polyfit is at its max is: %3.6f" % (max_xy_value))
sb.set_theme(style="white")
plt.scatter(x,y, color="r")
plt.plot(new_x, new_y)

#plt.legend(['Directional difference score', 'Directional polyfit 2dg'])
plt.xlim(-2.8,2.8)
plt.savefig('NoLine')
plt.axvline(x=max_xy_value, color='black')
plt.savefig('WithLine')
plt.show()
```