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Detecting Threats from Constituent Parts: A Fuzzy Signal Detection Theory Analysis of Individual Differences

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DETECTING THREATS FROM CONSTITUENT PARTS: A FUZZY SIGNAL DETECTION THEORY ANALYSIS OF INDIVIDUAL DIFFERENCES

by

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ABSTRACT

Signal detection theory (SDT) provides a theoretical framework for describing performance on decision making tasks, and fuzzy signal detection theory (FSDT) extends this description to include tasks in which there are levels of uncertainty regarding the categorization of stimulus events. Specifically, FSDT can be used to quantify the degree to which an event is 'signal-like', i.e., the degree to which a stimulus event can be characterized by both signal and non-signal properties. For instance, an improvised explosive device (IED) poses little threat when missing key elements of its assembly (a stimulus of low, but not zero, signal strength) whereas the threat is greater when all elements necessary to ignite the device are present (a stimulus of high signal strength). This research develops a link between key individual cognitive (i.e., spatial orientation and visualization) and personality (i.e., extroversion, conscientiousness, and neuroticism) differences among observers to performance on a fuzzy signal detection task, in which the items to be detected (IEDs) are presented in various states of assembly. That is, this research relates individual difference measures to task performance, uses FSDT in target detection, and provides application of the theory to vigilance tasks. In two experiments, participants viewed pictures of IEDs, not all of which are assembled or include key components, and categorize them using a fuzzy rating scale (no threat, low threat potential, moderate threat potential, or definite threat). In both experiments, there were significant interactions between the stimulus threat level category and the variability of images within each category. The results of the first experiment indicated that spatial and mechanical ability were stronger predictors of performance when the signal was ambiguous than when individuals viewed stimuli in which the signal was fully absent or fully present (and, thus, less ambiguous). The second study showed that the length of time a stimulus is viewed is greatest when the signal strength is low and there is ambiguity regarding the threat level of the stimulus. In addition, response times were substantially longer in study 2 than in study 1, although patterns of performance accuracy, as measured by the sensitivity index *d'*, were similar across the two experiments. Together, the experiments indicate that individuals take longer to evaluate a potential threat as less critical, than to identify either an absence of threat or a high degree of threat and that spatial and mechanical ability assist decision making when the threat level is unclear. These results can be used to increase the efficiency of employees working in threat-detection positions, such as luggage screeners, provides an exemplar of use of FSDT, and contributes to the understanding of human decision making.

This is dedicated to M.B. Burford

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CHAPTER 1: INTRODUCTION

Signal detection theory can be used to quantify performance of a perceptual task, and differences in that performance vary across task domains and individuals. The proposed research seeks to investigate a relationship between a person's characteristics and performance of a signal detection task in which stimuli consist of both signal and non-signal characteristics, only parts of a signal are present, as well as to investigate the relationship between duration of stimulus viewing time and signal ambiguity. A signal refers to a measurable event consisting of stimuli to be detected or discriminated. For such tasks, it is generally assumed that the signal may be masked by environmental conditions, some of which may manifest in similar form to the signal, or that internal processes of the operator (such as psychological state, previous experience or lack thereof, or random sensory processes) may interfere with proper detection performance; in either case, these distractors are referred to as the 'noise' in which signals are embedded (Green & Swets, 1966/1988).

Because one is trying to identify a particular object among many potential distractors, a model in which a signal is embedded in noise is an apt description for a variety of tasks that require one to distinguish signals from non-signals; examples include detection of defective products in an assembly line, a radar operator monitoring plane trajectories, or a doctor analyzing an x-ray to detect a cancerous growth. A large body of research has been dedicated to refining the ways in which performance of such detection tasks can be analyzed and quantified in an effort to maximize performance as a function of environmental conditions (Green & Swets, 1966/1988). The present study seeks to add to the literature a consideration of how the characteristics of the human observer affect task performance. A considerable number of studies have investigated the individual differences in human characteristics that may be related to performance evaluated in a traditional signal detection theory paradigm (e.g., Cox-Fuenzalida et al., 2006; Cox-Fuenzalida, Swickert, & Hittner, 2004; Frenkel et al., 2009; Rose et al., 2002; Singh, Molloy, & Parasuraman, 1993; Szalma, 2009a; Szalma, Hancock, Dember, & Warm, 2006; Szalma & Taylor, 2011). In many cases, the intention of this research is to identify the salient traits that may lead to efficacious screening procedures for employment of operators in the discrimination task, or for interface and training design (e.g., Szalma, 2009b).

Overview of Signal Detection Theory

In traditional signal detection theory, a decision is made regarding the presence or absence of a signal embedded in noise (e.g., an environment containing perceptual distractors). There are four possible outcomes of such a decision: a hit (responding affirmatively when a signal is, in fact, present), a miss (failing to detect a signal), a false alarm (responding affirmatively when no signal is present), or a correct rejection (responding that there is no signal when it is not present). Figure 1 is a representation of the described possible outcomes. A more detailed discussion of signal detection theory and all its assumptions follow in the literature review section.

		Response	
		Signal	Noise
State of the World	Signal + Noise	Hit	Miss
	Noise	False Alarm	Correct Rejection

Figure 1: Four Outcomes of a SDT task.

Uncertainty in Signal Detection Tasks

The observer in a signal detection task is asked to make a decision in a situation of uncertainty regarding signal absence/presence. This uncertainty arises because one of the tenets of the traditional signal detection theory paradigm is that there is uncertainty along the evidence variable where the noise and signal-plus-noise distributions are represented (Wickens, 2002). The noise that is always present in the system may be perceived by the operator as a signal (see the outcomes in Figure 1), but the noise itself does not, in reality, possess the primary characteristics that define the signal. While this certainly leads to a highly useful and accessible mathematical model, it fails to capture the reality of many of the situations the model is being used to quantify.

Many situations that lend themselves to a signal detection analysis have a signal that is not rigidly defined, but is dynamic in its formation thereby forcing a somewhat arbitrary line to be drawn to define signal versus non-signal. For example, the high breast density that is present in some women causes up to twenty percent of breast cancers to be missed during a diagnostic screening; on the other hand, tissue damage from previous biopsies or a patient's family history of cancer may cause a diagnostician to declare the x-ray abnormal when no cancer is present (National Cancer Institute, 2010). Thus, properties of the situation surrounding the decision (either external environmental properties or cognitive influences of the decision maker) introduce uncertainty by either camouflaging a legitimate signal or enhancing the signal-like properties of noise in such a way that the noise may be mistaken as a signal. This uncertainty may be exacerbated in the case where a signal can be decomposed; that is, if elements of a signal can be separated and presented in combinations that do not comprise a complete signal, it may be more difficult for the decision maker to accurately determine that a signal has been presented. In these circumstances, which occur in many operational environments (such as airport luggage screening in which a weapon could be transported through security in a disassembled form), fuzzy signal detection theory can be used to provide a more complete model of the detection process.

Fuzzy Signal Detection Tasks. Fuzzy signal detection theory extends traditional signal detection theory by allowing one to model uncertainty in the signal observed, the response of the observer, or both. Instead of stating that a signal is either present or absent, the perceiver has the option to state that the signal is present to varying degrees; that is, the human operator may characterize an event as being a 'partial signal', rather than being forced into the binary decision of signal or non-signal. This allows the observer to characterize the event in a manner in keeping with his perception when the stimulus itself is fuzzy (e.g., when an object has uses as both a weapon and a non-weapon, such as a razor blade contained in luggage), or to capture perceived uncertainty when the stimulus is wholly a member of either the category signal or non-signal, but the observer is influenced by noise (either internal or external) as to the state of the signal (e.g., a shadow on an x-ray may indicate a structure that has both cancerous and noncancerous properties).

The use of fuzzy signal detection theory to capture differing degrees of a signal has a wide variety of application, but has been limited to the contexts of vigilance (Stafford, Szalma, Hancock, & Mouloua, 2003), hazard perception (Lu, Hinze, & Li, 2011; Wallis & Horswill, 2007), and air traffic control (Masalonis & Parasuraman, 2003). The application of interest here is the use of signal detection theory to quantify performance of a threat detection task in which the potential "threat" itself has signal properties to differing degrees. For instance, individuals may be screened for potentially lethal contraband when entering a government building or before flying from an airport, but the military also screens environments for threats prior to entering an area. Of particular interest to this research is identifying threats assembled from common devices, known as improvised explosive devices (IEDs), or threats that are designed to fit into their surroundings. In these circumstances, individuals may need to recognize a threat based on its unassembled, constituent parts, which may not be present in totality; for example, Zorpette (2008) reported military raids in 2007 targeted at IED-making material (not the IEDs themselves). Because such tasks have an inherent amount of uncertainty (e.g., when material could be used for an IED but also has alternate legitimate purposes), fuzzy signal detection theory offers a more descriptive approach to analysis.

Individual Differences and the Proposed Experiments. Excessive quantities of materials used to make IEDs, such as that reported by Zorpette (2008) may be relatively easy to identify as a threat, however a disassembled explosive hidden in luggage, or across different parts (temporally or spatially) may be much more difficult. For instance, one could disassemble an explosive and store the pieces in separate parts of a room (or across multiple rooms or buildings); when viewed by a military search team, the observers may not be viewing these disassembled, separated pieces in the context in which they would normally be when assembled into a device. A task in which one must recognize a signal based on the presence of parts of the signal, which may be separated spatially and rotated from a standard position, depends in large part on the perception, and the appraisal of that perception, by the human observer. It is currently unknown whether two individuals would recognize such objects with equivalent speed and accuracy; consequently, performance of the task may vary as a function of individual differences among observers. Spatial orientation and visualization are factors that may influence successful mental rotation and (mental) reassembly of a device from constituent parts in an abnormal situation (either in position or state of assembly). Spatial orientation and visualization are, therefore, two of the specific individual difference measures that this research proposed to investigate.

In keeping with the concept of affordance (Gibson, 2003) and the famous quote of the Rationalist thinkers of Architecture and Design (derived from the words of Louis Sullivan) that "form follows function", many modern tools are designed in such a way that their purpose may be understood immediately by the user. When an object is disassembled, it may lose some key features that define the use of the object. For example, a disassembled IED may be stored so that the trigger and wires are spatially separated, with one of the two components perhaps not even visible to the observer; similarly, when in separate parts, a disassembled handgun does not clearly indicate which aspect of the implement is to be held versus which is to be the projectile conduit.

Costantini, Ambrosini, Scorolli, and Borghi (2011) concluded that object recognition is first conceived in terms of object use, which may be context dependent, but such isolated component presentation may detract from an individual's ability to recognize the potential use of the object as part of an IED. In fact, the more dissembled the presented object is, the more difficult it may be to recognize the threat. The research of Castelhano and Heaven (2010) support this line of reasoning in that the researchers found that speed of recognition is improved when the key features that define a target are present; the presence of target-feature information improved recognition speed with greater significance than even the context of scene. Thus, the absence of key features may have a profound impact on threat detection in situations of disassembly, regardless of the level of actual threat in the environment.

Further, Huang (2011) argues that object familiarity (e.g., knowing what a C4-based IED looks like) does not aid recognition of that object's individual constituent features; familiarity with the object, according to Huang, only contributes to recognition of an object as a whole. Compounding this potential for misidentification or lack of identification, Quinlan and Cohen (2011) demonstrated that response time is faster when more target features are present in the object to be inspected; in other words, the lower the number of available features (e.g., with a disassembled IED), the longer the response time necessary to identify that object. In many situations of imminent threat, our goal should be to shorten identification time as much as possible. Hollingworth and Henderson (2003) investigated the phenomenon that change detection is easiest when objects stand out from the scene and their results did not support use of short term memory, but rather the influence of context. While Hollingworth and Henderson's work may seem at first to contradict the findings of Castelhano and Heaven (2010), in fact it is supportive, pointing towards a hierarchy of contributive factors starting with key features of a target object, with contextual cues following, and most minimally the contribution of short-term memory.

Stimulus Viewing Time and Fuzzy Signal Detection Tasks. Arguments have been made that object categorization occurs simultaneously with object recognition (e.g., Grill-Spector & Kanwisher, 2005). However, de la Rosa, Choudhery, and Chatziastros (2010) asserted that there are differences in the response times associated with object detection, categorization, and identification. With a threat detection task, individuals must not only recognize and categorize objects, but they must also make a decision regarding the perceived level of threat the object(s) pose. For instance, it has been shown that dual target searches are less efficient than single target searches (Menneer et al., 2007); thus, one might speculate that, when searching for components of a target, the response time might correlate with the number of components (or distractors) present. Decision time regarding threat level may suffer considerably as a result. One purpose for the proposed work is to investigate whether a relationship exists between the fuzzy membership level of a stimulus, the perceived fuzzy membership level of a stimulus, and response time.

Spatial Orientation and Visualization and the Current Experiments

When spatially separated, the components of an object being viewed may be interpreted as potentially belonging simultaneously to multiple categories. It has been demonstrated that items near the boundaries of categories (such as faces and vowel sounds) have increased response time for discrimination (e.g., Bonnasse-Gahot and Nadal, 2011; Feldman, Griffiths, and Morgan, 2009; Kikutani, Roberson, & Hanley, 2008). As noted previously, objects may initially be recognized in terms of their typical or conventional use; thus, when category membership of the object is uncertain, an individual may need to perform mental rotations or alignments in order to ascertain the use of the object. Sun and Gordon (2010) demonstrated that spatial arrangement influences visual memory retrieval and change detection for an object's features is influenced by the orientation of the object. Smith and Dror (2001) speculated that individuals perform a piecemeal rotation of meaningful objects. Such manipulations may be aided by a high proficiency in either spatial orientation by way of aiding with recognition of object components and use, or visualization through aiding with transformations.

Spatial orientation and visualization were selected for the present investigation because both likely play a role in the ability to recognize objects that could be combined to create a threat. That is, an operator may need to mentally rotate one or more objects to match a preformed or pre-trained template from a mental catalogue to see if it can be matched to a component of an IED or other threat; the degree to which one is able to perform such mental manipulation is reflected in an individual's spatial orientation ability. Because IEDs can be constructed from common materials (The National Academies and the Department of Homeland Security, 2003), it may not be sufficient to recognize only constituent parts. An individual may need to mentally assemble the recognized parts of a threat to see whether they fit together in a way that would constitute a full signal or nearly a full signal; the degree to which one is able to perform a sequence of steps of cognitive processing is reflected in an individual's visualization ability.

Individual Differences in Personality Traits Related to the Task. It has been previously established that certain personality traits interact with some cognitive task characteristics to influence performance (e.g., Szalma, 2008, discusses research linking pessimism, optimism, and extraversion to performance on stressful tasks). Thus, the relation of both visualization and spatial orientation to performance may be influenced by specific personality traits, as well as the individual personality traits influencing performance; Finomore, Matthews, Shaw, & Warm (2009) adopting a resource theory perspective, suggest that personality traits that impact either resource availability (such as anxiety or extraversion) or voluntary commitment of resources (such as conscientiousness) may impact performance on a detection task. Tasks of vigilance (e.g., baggage screening) have been shown to be very cognitively demanding, and well modeled by resource theory (Warm, Parasuraman, and Matthews, 2008), thus personality factors should be considered individually and as possible mediators when investigating primary individual difference measures (and see Szalma, 2009a).

Research Aims

The purpose of the present research was to investigate the joint effects of fuzzy stimulus category and individual differences among participants that may affect performance of a signal detection task when the object representing a full signal is disassembled into its constituent parts, and all such parts may or may not be present when the stimulus is viewed; that is, the current study investigated three main issues: Individual differences in threat detection performance, use of FSDT in target detection, and characteristics of stimulus variability and fuzzy membership that affect performance. These studies analyze and describe performance on a fuzzy signal detection task with respect to both characteristics of the human operator and elements of the stimulus.

A threat decomposed into its constituent parts could potentially pose substantial threat in a military theatre or terrorism screening operation. For example, the safety of the general population is enhanced if airport screeners are able to identify individual parts hidden in carry-on luggage that can be assembled into a dangerous weapon; at the same time, it is a waste of resources to unnecessarily detain and search passengers when only a few of their possessions are able to be used as weapon parts, and not without vital components that are not present in their (or other passengers') luggage. Similarly, military personnel deployed in a foreign country may need to sweep a building for potential threats prior to entering; this may be accomplished either by sending troops into the building or through remote viewing with the aid of a robotic camera. Determining what areas of the building pose a substantial threat may be dependent upon correctly identifying pieces of weapons or IEDs that may be present in a cluttered environment. Thus, it is beneficial to know whether particular aspects of personality and/or cognitive ability are characteristic of an individual skilled in performance of such a fuzzy signal detection task.

In the present research, the task scenario depicted rooms in an office building which were swept for IED components using a simulated remote viewing device. The components of the IEDs were viewed by participants with the IEDs in various stages of assembly; these components were presented as photographs of typical office surroundings (cluttered environments). Additional items that can serve as potential distractors were included. Analyses of performance with regard to individual differences in visualization, spatial orientation, and three personality traits were performed. Relationships between the length of viewing time and ambiguity of the signal were explored in a second experiment.

CHAPTER 2: LITERATURE REVIEW

The current study examines both fuzzy signal detection theory (FSDT) and aspects of individual differences in human performance. Because fuzzy signal detection theory was derived from traditional signal detection theory, a brief discussion of the latter is warranted followed by a summary of FSDT. This chapter will then conclude with a review of individual differences directly related to the current research.

Signal Detection Theory

According to Swets (1973), the origins of psychophysics lie in the work of Fechner's measurement of the just noticeable differences (JNDs) between stimuli, the basic process of which was expanded by Thurstone (1927). With the development of electronic communication devices came the difficulty of analyzing the effects of noise in the system, and statistical decision theory was applied to this task in the mid-twentieth century, most notably by Blackwell (as described in Swets, 1973; see also Peterson, Birdsall, & Fox, 1954), who introduced the notion of an observer's use of a criterion in decision making. Psychologists at the University of Michigan continued to refine this theory to quantify descriptions between a physical stimulus and the perception of that stimulus (e.g., Tanner & Swets, 1954; Swets, Tanner, & Birdsall, 1961). Thus, it was in the realm of psychophysics that signal detection theory (SDT) was first applied in psychology.

Detection theory, as described by Green and Swets (1988/1966), involves dichotomizing the world into states of noise or signal plus noise; that is, human beings are inundated with sensory input, both internal and external, that in terms of performance of a specific task may be considered a distraction (or potential distraction) termed "noise". The noise present in any system is independent of the observer. A signal represents an occurrence of an event which does not occur in isolation but is embedded in the noise. For each trial the observer must decide whether the stimulus presented is a signal. Four outcomes are possible for each trial or observation (see Figure 1): the participant may respond that there is a signal when one is present (a "hit"); the participant may decide that there is a signal when one is not present (a "false alarm"); the participant may state there is no signal when there is in fact a signal present (a "miss"); or the participant may decide there is no signal when there is none (a "correct rejection"). Each of these outcomes has an associated probability: the hit rate (HR), the false alarm rate (FAR), the correct rejection rate (CRR), and the miss rate (MR).

Assumptions of Signal Detection Theory

In the traditional signal detection model, noise is assumed to be omnipresent, and the noise may be internal or external to the observer; the noise is assumed to be a normally distributed random variable. When a signal is present, the signal plus noise distribution retains the standard normal shape but is shifted along the sensory dimensions (see Figure 2); this is the equal variance assumption of SDT, i.e., that the variance of the signal and noise distribution is equal to that of the noise distribution. Another assumption is that the perceiver is both a sensor and a decision maker: When a stimulus is presented, the observer must accurately perceive the stimulus as either a signal or non-signal; but the observer also sets a criterion by which he will make his decision of signal or non-signal. The sensitivity of the observer refers to his perceptual ability to distinguish the signal from the background noise; the most commonly used mathematical quantity representing the sensitivity is d', defined as the distance (in standard deviations) between the noise curve and the signal plus noise curve. Response bias refers to the observer's willingness to label an event as signal present, and may vary as a function of the relative cost of misses and false alarms; for example, one may have a more liberal response bias when evaluating spots on an x-ray as potentially cancerous growths figuring that a propensity to biopsy unnecessarily is a lesser evil than possibly missing a truly cancerous growth. The parameter β (or $\ln\beta$) is used to represent the response bias although in some instances, such as vigilance, the criterion index c is superior to β or $\ln\beta$ (See, Warm, Dember, and Howe, 1997). In SDT, the sensitivity and response bias of the observer are assumed to be independent of one another.

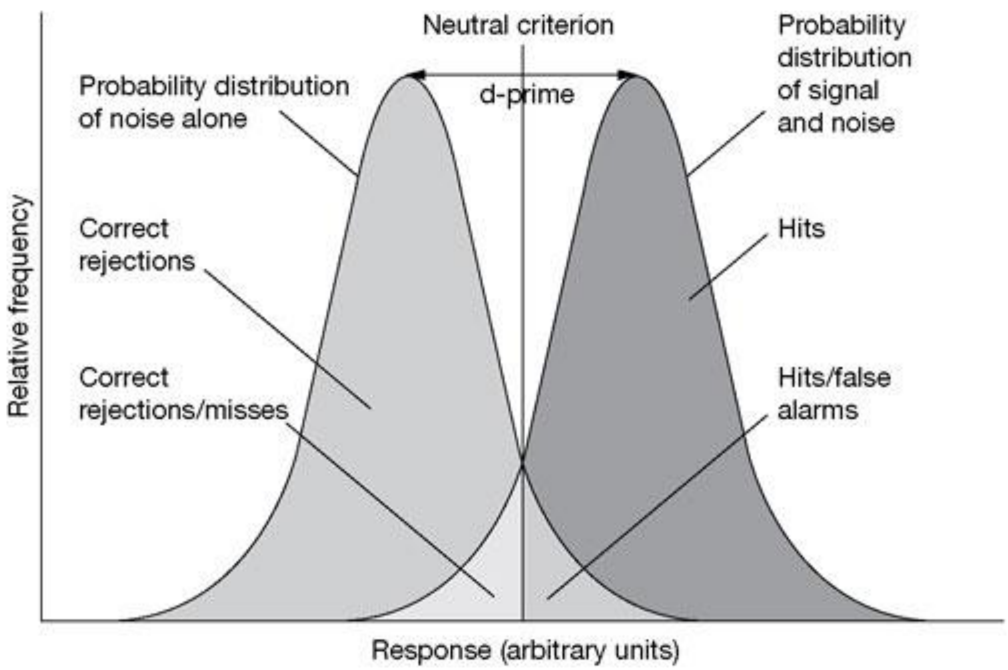


Figure 2: Graphical representations of response categories for traditional SDT

Retrived from http://www.nature.com/ncpneuro/journal/v4/n6/images/ncpneuro0794-f1.jpg

Limitations of Signal Detection Theory

SDT has proved to be a useful and appropriate tool for a variety of applications (Swets, Dawes, & Monahan, 2000). However, there are some situations in which the theory does not capture the complexity of the stimulus and/or perceptual process. A primary limitation of traditional SDT is that it forces both the state of the world and the response of the observer into mutually exclusive categories, often the dichotomy of presence of signal or absence of signal. That is, an item that has properties of multiple categories cannot be easily represented in the traditional model; in the dichotomy, the item is either a signal or it is not, with no intermediary categories. Forcing descriptions into mutually exclusive categories is not always reflective of occurrences in operational environments. Many signals retain properties of a non-signal, such as a yellow traffic light that signals that one should be cautious (not that one should stop). Parasuraman, Masalonis, and Hancock (2000) developed Fuzzy Signal Detection Theory (FSDT) to address this limitation (and see Hancock, Masalonis, and Parasuraman, 2000).

Fuzzy Signal Detection Theory

FSDT is based on set theory principles developed in the application of fuzzy logic. In traditional set theory, an item is either an element of a set or it is not; for example, ½ is an element of the set of "rational numbers" because it has a representation as the ratio of two whole numbers, whereas π is not an element of this set because it fails that criterion. This is the approach adopted in traditional SDT—an item is either a member of the crisp set 'signal' or of the set 'non-signal'.

Elements of fuzzy sets, on the other hand, have degrees of membership to the set, rather than absolute classification of member or nonmember (Zadeh, 1965). Applying this concept to signal detection theory, an item can simultaneously have properties of both a signal and a non-signal, to varying degrees. For example, explosive material paired with wires alone cannot be considered a complete IED if the detonator is missing; however, this is clearly not innocuous material. Thus, that combination of items has certain properties of the set 'signal', without being a full signal. The same set of items can also be considered to have properties of the set 'non-signal' because it is missing the detonator. The degree of membership in a set can be represented with a number between zero and one, with zero corresponding to no membership and one corresponding to full membership in the set ‘signal’. For example, explosive material paired with wires might be considered to have degree of membership 0.8 in the set ‘signal’ and membership 0.2 in the set ‘non-signal’ (numbers arbitrarily assigned for discussion purposes). This provides a numeric description that the combination of items discussed is much closer to being an actual IED than it is to being no threat whatsoever. Such a numerical assignment of category membership can be carried out through use of a mapping function, example procedures for which are discussed by Parasuraman, Masalonis, and Hancock (2000).

In addition to the properties inherent to the object that assign it category membership to varying degrees, the observer’s response is also not necessarily confined to being binary and may differ in perceived degree of signal from that assigned to the stimulus. Specifically, participants are responsible for both sensing and categorizing the stimulus, but the categorization is no longer necessarily binary (although it can be — it should be noted that FSDT is also well suited for the case where the observer must make a binary choice (signal or non-signal) but the stimulus may be defined as a fuzzy set; Szalma & Hancock, 2013; Szalma, Oron-Gilad, Saxton, & Hancock, 2006). If the desired response is not binary, then observers in the signal detection task will need to assign a membership level to each observed stimulus along a range of values that can be transformed to numbers between 0 and 1, where 0 represents that the stimulus has no properties of a signal and 1 indicates that the stimulus is a signal with no membership in the non-signal category; that is, the observer is deciding *signal membership* along a continuum (that may be discrete or continuous, depending on the application).

Because degrees of membership in the category ‘signal’ or ‘non-signal’ are allowed, Hancock, Masalonis, and Parasuraman (2000) redefined what constitutes the traditional four outcomes of hit (H), miss (M), false alarm (FA), and correct rejection (CR). When a stimulus belongs to the category signal with membership level s, $0 \leq s \leq 1$, and the perceiver responds that the stimulus belongs to the category signal with membership level r, $0 \leq r \leq 1$, then the four outcomes are calculated by the following formulae (mixed implication functions; Parasuraman et al., 2000):

$$H = \min(s, r) \tag{1}$$

$$M = \max(s - r, 0) \tag{2}$$

$$FA = \max(r - s, 0) \tag{3}$$

$$CR = \min(1 - s, 1 - r) \tag{4}$$

An event in FSDT may have membership in more than one of the four categories of hit, miss, false alarm, and correct rejection. For example, if a strong signal is present, but an observer identifies a weak signal as being present, then the observer has made a certain degree of hit (signal present) and a certain degree of miss (the stimulus was not perceived as being as 'signal-like' as it actually is). Parasuraman, Masalonis, and Hancock (2000) asserted that β and d' can be computed using the same formulae in both traditional SDT and FSDT, formulae which involve the hit rate and false alarm rate. Murphy, Szalma, and Hancock (2003; 2004) demonstrated that FSDT provides a better description of an observer's sensitivity and response bias than crisp SDT when the stimulus is not a member of a binary category (signal versus non-signal; see also Szalma & Hancock, 2013; Szalma et al., 2006).

As with traditional SDT, it is assumed that noise can be internal (to the system or individual) or external. Also, both noise and signal plus noise have been shown to be normally distributed in FSDT (Murphy, Szalma, & Hancock, 2004; Szalma et al., 2006; Szalma & Hancock, 2013; Szalma & O'Connell, 2011). Noise may occur in any sensory medium, but it is most troublesome when it manifests in the same sensory channel as the one used for the detection task (e.g., a visual detection task is most disturbed by visual noise as opposed to auditory noise, except in that such may cause a break in visual attention), as this is a common component of many working memory models (e.g., the model of Baddeley and Hitch, 1974; 1986). In any detection task, the nature of the noise present in an event may contribute to a delay in response by the observer; the degree of membership of the stimulus in FSDT may allow some useful characterizations of the stimulus to be made.

Fuzzy Membership Level and Observer's Response Time

Response time has importance in detection theory. Hancock, Masalonis, and Parasuraman (2000) concluded, based on the research of Treisman and Gelade (1980), that it takes longer for the human cognitive system to reach a decision of non-signal than it does to reach the decision of signal, particularly when abundant noise is present within, or simultaneous to, a stimulus presentation. The authors reasoned that SDT decisions made the most rapidly (on average across trials) would have the highest numbers of false alarms, decisions near the average decision time for the observer would have the highest numbers of hits, and the longest decision times would have the highest numbers of correct rejections and misses (though more correct rejections than misses). Hancock, Masalonis, and Parasuraman asserted that the same pattern emerges in FSDT.

The length of time until response in traditional SDT is related to the ambiguity of the stimulus; in FSDT, the fuzzy membership level reflects this property of the stimulus. Thus, the time to decision in a detection task should be related to the degree of membership in the category signal that the participant perceives and/or the degree of membership in the category signal that the stimulus actually possesses, although the degree to which this relationship is evident may depend on the nature of the stimulus. That is, a stimulus that has very low or very high membership (or perceived membership) in the category signal may often be associated with a shorter response time by the observer than a stimulus that has (or is perceived to have) a signal membership closer to the 0.5 level.

One can then speculate how such a relationship can be quantified. The present research examined a specific instance with application: when the stimulus is a decomposed IED, which may generalize to any decomposed weapon. Should it prove to be the case that longer decision times are associated with somewhat strong signal membership, one application of this fact would be to design a system in which any rating that is abnormal for the given decision time would be flagged for further inspection of the stimulus or event. Note that such a relationship would also have the benefit of providing an efficiency rating of the observer or system; any instance in which such abnormal ratings were routine would identify the system or observer as being in need of redesign or remediation, respectively.

Individual Differences

Sometimes two participants will perform differently on identical tasks, or provide different reactions to identical stimuli, because of different personality or cognitive traits that vary across individuals and influence perception and cognition. In psychology, the study of these individual differences can improve explanation and prediction of performance (Cronbach, 1957; 1975; Underwood, 1975). As Cronbach (1956) described, "… personality theory is applied to weave nomothetic constructs into a construct of the individual's personality structure, predictions are then derived by inferring how that structure will interact with the known or guessed properties of the situation" (p. 173). In other words, Cronbach acknowledged that performance prediction is an interweaving of time, personality features, individual capacities for performance, and even such nuances as inclination to perform at a particular time, amongst other factors. The end result is the *generalized* ability to predict performance, which is, and must always be, a somewhat fluid and labile construct by its very nature, as there are too many confounds to performance to allow precision.

Because of these individual differences, performance on a detection task varies not only with the nature of the task or the stimulus but also with the characteristics of the individual observer. For instance, one observer may set a different criterion than another observer under the same task conditions, or there may be vast differences in the sensitivity of individual observers. Such variations are nearly unavoidable, and while there will always be, where human performance is concerned, a *deus ex machina* that results in perturbations of expected performance despite all efforts to impose constraints, it appears the degree to which observers vary in their response bias or sensitivity is impacted significantly by relevant cognitive or personality traits. These personal characteristics can be used to generate a model with reliable accuracy and predictive ability. For these reasons, the present research is concerned with the influence of traits of personality as well as the cognitive abilities of visualization and spatial orientation on performance of an IED detection task.

Personality traits. Five emergent factors of personality were first identified by Tupes and Christal (1961/1992) and later replicated by Norman (1963). The NEO Personality Inventory was developed as a measure to quantify an individual's placement along the dimensions, and is widely used in clinical and research settings (Costa and McCrae, 1992) for both adolescents and adults (e.g., Decuyper, De Bolle, Boone, and De Fruyt, 2012; Langer, 2011; Betz and Borgen, 2010; Kotov, Gamez, Schmidt, and Watson, 2010; Hoffman, Buteau, and Fruzzetti, 2007). The five factors of the model measured by the NEO-PI are extraversion, agreeableness, conscientiousness, neuroticism, and openness to experience. Table 1 lists adjectives McCrae and John (1992) identified to describe the positive poles of the personality scales. Data from diverse populations indicate that the five-factor model is an apt representation of personality characteristics regardless of background and culture (McCrae and Costa, 1997). Three of the five factors (extraversion, conscientiousness, and neuroticism) will be measured for this research, as these are the traits that have been shown to influence performance on signal detection tasks, particularly in vigilance.

Table 1. Adjectives McCrae and John (1992) used to describe NEO-PI personality traits

Personality Factor	Adjectives
Extraversion	"active, assertive, energetic, enthusiastic, outgoing, talkative"
Agreeableness	"appreciative, forgiving, generous, kind, sympathetic, trusting"
Conscientiousness	"efficient, organized, planful, reliable, responsible, thorough"
Neuroticism	"anxious, self-pitying, tense, touchy, unstable, worrying"
Openness to Experience	"artistic, curious, imaginative, insightful, original, wide interests"

Personality and Vigilance. Several studies have investigated the relationship between the five-factor model and performance in a vigilance or detection task. Matthews and Campbell (2009) reported that standard personality traits are weak predictors of vigilance performance, with extroversion and neuroticism showing unique, but small, contributions to prediction of performance (see also Finomore et al., 2009). Rose, Murphy, Byard, and Nikzad (2002), however, reported that both extraversion and conscientiousness correlated with performance while neuroticism correlated with aspects of perceived workload. More recent evidence suggests that these effects may be linked to specific facets of the broader trait (Teo, Szalma, and Schmidt, 2011).

Extraversion. Davies and Parasuraman (1982) and Finomore, Matthews, Shaw, and Warm (2009) summarized research that indicates introverts tend to have more correct rejections, fewer false alarms, and experience less decrement in detections than extroverts; similar findings are summarized by Berch and Kanter (1984) who further cite research indicating introverts may have different sensitivity thresholds than extroverts. In a task of auditory vigilance, it has been shown that performance decreases as workload decreases in extroverts, but the same decline in performance is not seen in introverts (Cox-Fuenzalida et al., 2006). According to Eysenck (1989), who performed a summary of relevant literature investigating the relation of extraversion to vigilance, introverts generally outperform extroverts in vigilance tasks and tend to show a smaller vigilance decrement.

Koelega (1992) performed a meta-analysis on the relationship between extroversion and vigilance performance and found that the literature suggests that extroverts underperform introverts. It should be noted that there are instances in which no correlation between performance and introversion-extroversion was observed, such as Singh, Molloy, and Parasuraman (1993), where participants monitored for automation failure in either a fixed-rate or variable condition; in this study, performance was found to be related to complacency potential and energetic-arousal, however. Szalma and Taylor (2011) also reported no performance effects for extroversion during a monitoring task with an automated aid.

Neuroticism. Cox-Fuenzalida, Swickert, & Hittner (2004) showed that high levels of neuroticism are associated with delayed reaction times in an auditory vigilance task. Additionally, individuals high in neuroticism exhibited a decline in performance when workload levels were increased. Szalma and Taylor (2011) reported a similar drop in performance for individuals high on neuroticism. Eysenck (1989), however, argued that there is little evidence for the influence of level of neuroticism in task performance on a vigilance task, suggesting that the attentional differences between individuals high and low on neuroticism are not affected by the situational anxiety associated with a vigilance task.

Conscientiousness. Higher levels of conscientiousness have been associated with a conservative response style in signal detection tasks. Rose et al. (2002) found that individuals high in conscientiousness tended to commit fewer false alarms and achieved greater perceptual sensitivity. Burton et al. (2010) investigated the effects of gender and personality on a vigilance task. Across genders, the study demonstrated that higher conscientiousness was associated with more conservative response bias. However, the relation of conscientiousness to cognition has not been explored as extensively as extraversion and neuroticism (Matthews, Deary, & Whiteman, 2009).

Cognitive Abilities. The personality traits discussed may influence performance directly, or they may moderate the effects of cognitive abilities (e.g., Arana, Meilan, and Perez, 2008). The two cognitive abilities that may play an important role in the present research are spatial orientation and visualization. Spatial orientation is identified as a possible predictor of performance when a task may require mental rotation and alignment to see if parts fit to a preprogrammed template. Visualization is reflective of one's ability to manipulate an object in an ordered sequence of steps, a skill necessary to correctly assemble devices from constituent parts. Because the current research is focusing on performance of threat detection when various parts that can be used to assemble an IED are presented, both spatial orientation and visualization will be investigated to determine their relation to performance.

Spatial cognition refers to an individual's knowledge about the spatial properties of objects, locations, and events (Montello, 2001). It is generally accepted that spatial ability is composed of distinct factors (e.g., McGee, 1979), though it should be noted that an argument has been made to the contrary (e.g., Colon et al., 2001). Spatial orientation and visualization, as measured by the Kit of Factor-Referenced Cognitive Tests (Ekstrom et al., 1976) are the factors of spatial ability adopted for the present research. As shall be discussed, both factors may influence a task in which one is asked to assess a potential threat in its decomposed state (e.g., an unassembled IED).

Spatial Orientation. It has been demonstrated that individuals high in visual working memory capacity differ in performance of a visual search when that search relied on top-down processing (Sobel, Gerrie, Poole and Kane, 2007). Bottom-up attentional processes are involved when items stand out from their surroundings whereas top-down mechanisms access knowledge stores to draw attention to items important to the observer (Connor, Egeth, and Yantis, 2004). Because a detection task requires individuals to focus attention on specific object properties (rather than just the most salient feature), one might speculate that certain signal detection tasks (e.g., FSDT tasks) would demonstrate changes in sensitivity as a function of individual differences in visual working memory (as well as spatial processing and mental rotation). For example, a significant difference may not exist in the case where an x-ray is being analyzed for a cancerous growth (parallel to bottom-up processing where one looks for an abnormality to present itself) but may be prevalent when searching for the components of a weapon that has been broken down and stored in luggage (requiring top-down processing where one must be able to detect objects key to the weapon assembly that may not necessarily be salient parts); additionally, in the latter the observer may need to perform mental rotation and reassembly of the components.

Before one could mentally reassemble the parts, however, those parts must be recognized within the scene by the observer. Performance on this process of recognition may vary across or within individuals when the objects viewed are at dissimilar orientations to the templates they have stored in memory. All theories of object recognition require that a match take place between the viewed image and an item in the individual's knowledge store, but theories differ as to whether that recognition is viewpoint dependent. Viewpoint invariant theories, such as Biederman's (1987) theory of recognition by components, hold that object recognition will take place regardless of the observer's viewing relation to the object, and some studies have supported such a theory (e.g., Biederman and Gerhardstein, 1993).

Evidence has been reported, however, for the contrary view—that recognition depends on the position and orientation of the object when viewed (e.g., Tarr, 1995; Tarr and Pinker, 1989; Willems and Wagemans, 2001). Tarr and Pinker (1989) argued that evidence suggests that an individual must mentally rotate an object to match one of possibly several orientations of the object in memory in order for recognition to occur. Even when objects are presented together, there is a time delay in matching rotated shapes; Shepard and Metzler (1971) identified a linear increase in time to recognition of objects as being the same with angular displacement between the representations in a matching task (not a recognition task) and Larsen and Bundesen (1998) demonstrated that individuals may mentally translate and rotate objects to determine sameness in a pattern matching task. Thus, in a situation where one is attempting to mentally reconstruct an object from its constituent parts, if the positions of those parts are not aligned with the template, a mental rotation (and possible translation) may need to occur in order for the observer to recognize the object.

Interestingly, Manning and Leach (2002) found a negative correlation between spatial reasoning ability and diagnostic performance in a mammography screening task. The researchers hypothesized that individuals high in spatial reasoning may have introduced more errors by attempting to manipulate the image being viewed.

The task proposed in this research will require mental rotation and manipulation, should one attempt to mentally reconstruct the decomposed IED from the constituent parts presented. Thus, the assessment of spatial ability in this task needs to involve mental rotation. The spatial orientation factor of the Kit of Factor-Referenced Cognitive Tests (Ekstrom et al., 1976) uses a card rotation test and a cube comparison test to assess one's ability to spatially manipulate an object as a whole. Hogan (2012) reported that these tests load on a single factor with acceptable reliability.

Visualization. In addition to spatial orientation, visualization may affect performance in a task where one is required to recognize the parts necessary to make a potential threat function properly. When an object is disassembled, it may take several sequential transformations of the components to mentally reassemble; when one or more components are absent, this mental reassembly may be necessary to determine whether enough of the object is present for it to retain its functional properties. Cheung, Hayward, and Gauthier (2009) found that object recognition was dependent upon image features; thus, one may need to see, through mental manipulation, whether constituent parts fit together to form what resembles enough of an image to fit into the category. That is, mental assembly of the object may be required to determine how much of a signal the decomposed, separated parts represent.

Thus, individuals high in visualization ability may be better able to identify which parts fit together and whether those parts can be properly combined to assemble a weapon. Spatial visualization has been found to be related to mental animation (Hegarty and Sims, 1994) and evidence has been provided for mental simulation as a strategy in mechanical reasoning tasks (Hegarty, 2004). Mechanical comprehension has already been demonstrated to correlate with performance in a weapons-handling task (Munnoch and Bridger, 2008); the task proposed in this research differs in that participants will not be directly instructed to assemble a weapon (in this case, an IED), though they may mentally do so in providing their ratings of the stimuli (in order to assist with template matching of threat level). Thus, individuals high in visualization may possess a superior ability to run mental simulations (including ones involving object assembly) thus leading to better performance on the present detection task.

The Kit of Factor-Referenced Cognitive Tests (Ekstrom, 1976) uses the form board test, paper folding test, and surface development test to measure the factor of visualization. Carroll (1990) confirmed the Kit's measures of two distinct factors in visualization and spatial orientation. This instrument has been used in establishing the structure of the ASVAB, Armed Services Vocational Aptitude Battery (Augustin, Gillet, and Curran, 1989) as well as studies linking spatial ability to a performance measure (e.g., Pak, Rogers, and Fisk, 2006; Lee and Shin, 2011).

Current Study

Performance of a signal detection task, where the signal is presented in constituent parts separated spatially and which may require rotation or physical manipulation to assemble, may vary as a function of individual differences in spatial orientation, visualization, the personality traits of extraversion and conscientiousness, or interactions between cognition and personality traits. Specifically, the literature indicates that individuals high in spatial orientation or visualization may outperform those low in these characteristics in correctly identifying disassembled signals. Further, because research has shown that extraversion and conscientiousness tend to correlate with performance on a signal detection task, it is believed that these factors may influence performance even among those high in spatial orientation or visualization. Figure 3 provides a model of the hypothesized relationships among the variables.

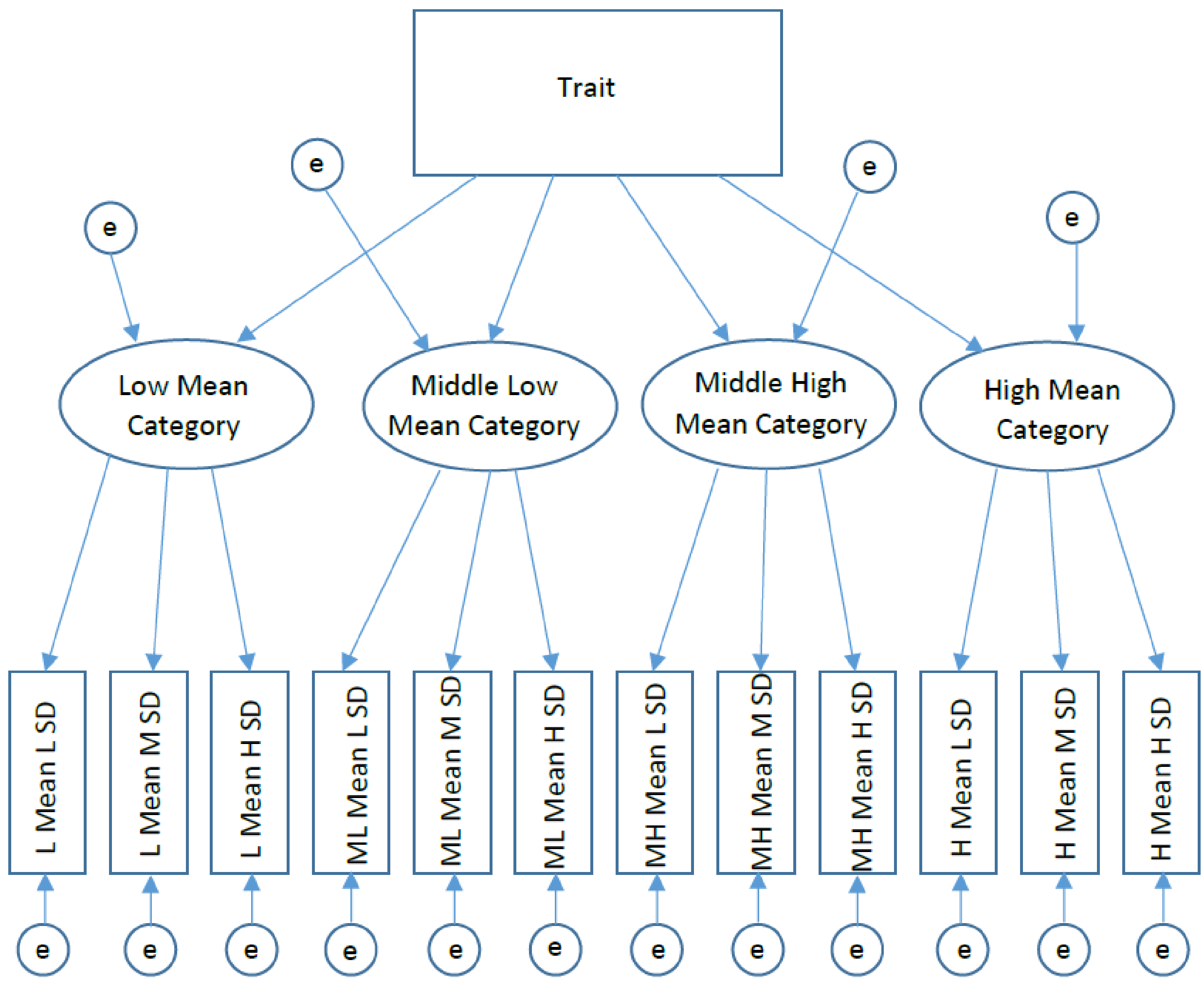


Figure 3. Hypothesized SEM model for each individual cognitive trait

H = High, M = Middle, L = Low, SD = Standard Deviation, e = error

Additionally, it is hypothesized that a relationship exists between the level of fuzzy membership of a stimulus, the length of time a participant views the stimulus before response, and the hit and false alarm rate of the participant. Specifically, it is conjectured that both stimuli close to full membership in the signal category (i.e., stimuli with a fuzzy membership close to 1) and stimuli close to no membership in the signal set (i.e., stimuli with a fuzzy membership in the category of signal close to 0) should require the least amount of viewing time and stimuli nearest to the middle (i.e., stimuli with a fuzzy membership in the category signal of close to 0.5) should require the greatest amount of viewing time prior to the participant's response. It is expected that a plot of average viewing time against fuzzy membership category across a range of stimuli can be fitted with a function whose maximum value is obtained when the stimulus is near a fuzzy rating of 0.5 (see Figure 4 for a sketch of the predicted model). Based on the postulates of Hancock, Masalonis, and Parasuraman (2000), it is further conjectured that the greatest hit rate will occur during the middle viewing time and the extrema of the false alarm rate will occur near the longest and shortest viewing times.

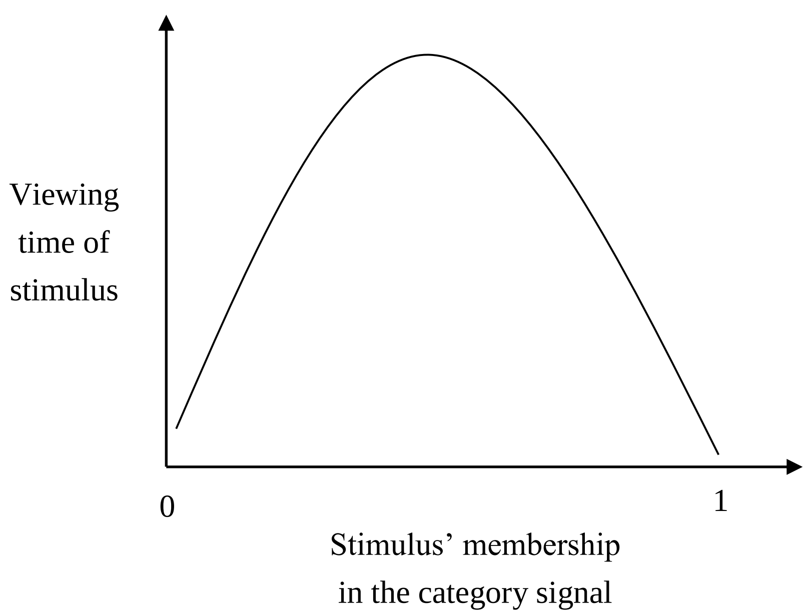


Figure 4: Hypothesized relationship between stimulus' signal membership and viewing time

In summary, it is hypothesized that performance on a threat detection task in which the threat is presented in a disassembled state:

- May improve with spatial orientation, visualization, or both;
- May be positively correlated with the personality trait of conscientiousness and negatively related to extroversion and neuroticism;
- May further correlate with interactions between the above listed cognitive abilities and personality traits;
- May be predicted in part by the ambiguity of the stimulus, and that this may be fitted with a quadratic or other curvilinear function.

The first hypothesis was investigated using a customary time-restricted forced-response detection task (Experiment 1) whereas the second hypothesis was investigated using a forced-response that was not time restricted (Experiment 2). As such, the current research consisted of two separate experiments using the same stimuli. The first experiment examined the relationship between performance and the previously identified individual differences. The second experiment examined the relationship between viewing time of the stimulus and the participants' response.

CHAPTER 3: PREVIOUS EXPERIMENT

Prior to the present work, an unpublished study was conducted in which mean ratings of threat level were obtained for the stimuli to be used in both experiments. Approximately 242 undergraduates at the University of Central Florida viewed the stimuli at three different durations, and provided a fuzzy response category rating of each photograph at each of the three speeds (700 ms, 1000 ms, and 1300 ms). Participants were provided instructions similar to those described in Experiment 1. Participants were also provided the visual color coding on the keys using the same categories as described in Experiment 1.

This preliminary study employed the same stimuli used in experiments 1 and 2. The data from that initial work were analyzed in terms of the mean fuzzy category rating and the variability associated with each photograph at each presentation duration. The photographs were then grouped by mean and further subdivided by variability. Four groups were thus created: low stimulus mean (M = 1.298, SD = .112), middle low stimulus mean (M = 1.990, SD = .283), middle high stimulus mean (M = 2.945, SD = .294), and high stimulus mean (M = 3.726, SD = .114). Definitions of low, medium, and high stimulus variability were dependent upon the stimulus mean category, as shown in Table 2.

Table 2. Range of Stimulus Standard Deviations by Mean Category

	Low Mean Category	Middle Low Mean Category	Middle High Mean Category	High Mean Category
Low Variability	0.41 – 0.53	0.67 – 0.78	0.68 – 0.80	0.39 – 0.51
Medium Variability	0.54 – 0.66	0.79 – 0.90	0.81 – 0.93	0.52 – 0.64
High Variability	0.67 – 0.79	0.91 – 1.04	0.94 – 1.06	0.65 – 0.79

In this experiment, participants had four choices of response. The instructions for the experiment (see Appendix A) explained that the lowest category represented a certainty that there was an absence of threat, the next category represented a low presence of threat, the next category a high level of threat, and the last category a definite presence of threat. Thus, when stimuli were divided into low, middle low, middle high, and high categories, the divisions were intended to reflect the described threat levels. Thus, an unequal partition of the stimulus mean ratings (1 – 4) was developed: the low stimulus mean category consisted of pictures with means between 1.0 and 1.49, the middle low stimulus mean category had means between 1.5 and 2.49, the middle high stimulus mean category had means between 2.5 and 3.49, and the high stimulus mean category had means between 3.5 and 4.0. Eight pictures were randomly selected from each of the twelve categories (mean by standard deviation) for use in the current study. Response times from this previous study were also used to determine the viewing length in the first experiment of the current research.

CHAPTER 4: RESPONSE SET DETERMINATION

An initial study was conducted to investigate the number of response choices required to capture sufficient variability in the fuzzy signal detection task of IED ratings. Response variability was evaluated by determining the effect of response set size on the discriminability among stimulus categories. Participants were presented the set of pictures 3 times, and asked to rate them using 4, 7, and 10 response choices. Participants were randomly assigned to one of the six possible orders of 4, 7, and 10 response choices. A total of 33 individuals participated in this pilot study. The results indicated that relatively comparable levels of discriminability were observed across the three response set sizes. As a result, 4 category choices were used in subsequent studies.

Methods

Participants. A total of 33 undergraduates (25 female, 8 male) at the University of Central Florida participated in the study, ranging in age from 18 to 29 (M = 19.12, SD = 0.376). All participants were recruited using the SONA system and were screened for normal or corrected-to-normal vision.

Procedure. Participants viewed 96 photographs of components (or distractors) of mock IEDs in a typical office building environment three times. The Fuzzy membership category values for the stimuli were established in a previous study using mean ratings of 242 undergraduate students at the University of Central Florida (see Chapter 3). The photographs used from this previous study were representatives of both mean category rating, and standard deviation within that category as divided by three approximately equal intervals. Within each of four mean categories, eight photographs of low standard deviation, eight photographs of medium standard deviation, and eight photographs of high standard deviation were selected. Each of those groups (containing the eight photographs) were further partitioned by the z-scores of the standard deviations from the mean standard deviation within the group in such a way that two photos with z-scores below -0.5, four photos with z-scores between -0.5 and 0.5, and two photos with z-scores above 0.5 were selected. Stimuli were presented to the participants on a standard desktop computer.

Participants completed an informed consent and a brief demographic questionnaire. Participants were then presented with a set of instructions describing the task and presented with the opportunity to ask questions. Each image was presented for 1600 ms, a length slightly longer than the length used in the previous study and the length of viewing that was used in all subsequent experiments, and participants were instructed to rate the image on one of three scales (a 4 point scale, a 7 point scale, and a 10 point scale). Each image was followed by a response screen that contained a visual image of the scale the participant was to use to rate the image. Participants were randomly assigned to one of the six possible ordering conditions of the three response scales. At the conclusion of the experiment, the participants were debriefed.

Results

In analyzing the data, Greenhouse-Geisser was used to correct for violation of sphericity in all F tests involved; the uncorrected degrees of freedom are reported as well as the epsilon used for the correction. Participant responses were analyzed with a three-way analysis of variance comprised of three levels of response choice (4 choices, 7 choices, 10 choices), three levels of stimulus variability (low, medium, high; see Table 2), and four levels of stimulus mean rating (1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0). All main effects and interactions were statistically significant at the .05 significance level (see Table 3).

Table 3. ***Omnibus ANOVA for Stimulus Ratings***

Effect	*df*	*ε*	*SS*	*MS*	*F*	*p*	η_p^2
Response Choices	2	.731	2288.604	1144.302	664.748	<.001	.954
Error	64		110.170	1.721			
Stimulus Mean	3	.617	3794.373	1264.791	314.939	<.001	.908
Error	96		385.535	4.016			
Stimulus Variability	2	.852	19.560	9.780	20.410	<.001	.389
Error	64		30.667	.479			
Response Choices*Stimulus Mean	6	.450	625.910	104.318	183.895	<.001	.852
Error	192		108.916	.567			
Response Choices*Stimulus Variability	4	.734	4.100	1.025	6.124	<.001	.161
Error	128		21.425	.167			
Stimulus Mean*Stimulus Variability	6	.538	128.673	21.446	41.325	<.001	.564
Error	192		99.638	.519			
Response Choices*Stimulus Mean*Stimulus Variability	12	.521	17.449	1.454	8.074	<.001	.201
Error	384		69.154	.180			

Additional ANOVAs were computed to further investigate the observed interactions; a 4 (stimulus mean rating: 1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0) x 3 (stimulus variability: low, medium, high) ANOVA was computed for each level of response choice (4 choices, 7 choices, 10 choices). The ANOVAs revealed significant main effects for stimulus mean, significant main effects for stimulus variability, and significant interactions of stimulus mean and stimulus variability across all response sets (see Table 4).

Table 4. ***4 x 3 ANOVAs for Stimulus Ratings with Each Response Set Condition***

Effect	Response Set Size	*F*	*p*	η_p^2	ε
Stimulus Mean	4	$F(3, 96)=294.707$	<.001	.902	.690
	7	$F(3, 96)=288.430$	<.001	.900	.735
	10	$F(3, 96)=284.104$	<.001	.899	.585
Stimulus Variability	4	$F(2, 64)=9.810$	<.001	.235	.932
	7	$F(2, 64)=12.192$	<.001	.276	.826
	10	$F(2, 64)=16.413$	<.001	.339	.908
Stimulus Mean*Stimulus Variability	4	$F(6, 192)=28.874$	<.001	.474	.520
	7	$F(6, 192)=29.354$	<.001	.478	.595
	10	$F(6, 192)=26.696$	<.001	.455	.656

For each response set condition, the significant stimulus mean by stimulus variability interaction was explored by computing one-way ANOVAs of the effect of stimulus mean within each level of stimulus variability. For each response set, there was a significant effect for stimulus mean across all conditions of stimulus variability (see Table 5). To ensure adequate variability across response set conditions for the subsequent experiments, the two-way interaction was also analyzed by computing one-way ANOVAs on the effect of stimulus variability within each level of stimulus mean for each response set condition. Although a nonstandard practice of analysis, it was deemed appropriate in this instance to explore the interactions in both directions in order to more fully evaluate the variability across the response sets. Each response set showed a significant effect for stimulus variability across mean rating categories, with the exception of 7 response choices at the highest mean rating category (see Table 5).

Table 5. ***One-way ANOVAs for Stimulus Rating within Each Response Set Size Condition***

Effect	Condition	Response Set Size	F	p	η_p^2	ε
Stimulus Mean	Low Variability	4	$F(3, 96) = 322.461$	<.001	.910	.660
		7	$F(3, 96) = 314.894$	<.001	.908	.791
		10	$F(3, 96) = 276.041$	<.001	.896	.651
	Medium Variability	4	$F(3, 96) = 202.079$	<.001	.863	.831
		7	$F(3, 96) = 187.801$	<.001	.854	.831
		10	$F(3, 96) = 202.371$	<.001	.863	.647
	High Variability	4	$F(3, 96) = 133.711$	<.001	.807	.813
		7	$F(3, 96) = 153.241$	<.001	.827	.831
		10	$F(3, 96) = 177.841$	<.001	.848	.766
Stimulus Variability	Mean 1.0 – 1.49	4	$F(2, 64) = 23.600$	<.001	.424	.687
		7	$F(2, 64) = 34.360$	<.001	.518	.801
		10	$F(2, 64) = 19.103$	<.001	.374	.756
	Mean 1.5 – 2.49	4	$F(2, 64) = 20.637$	<.001	.392	.786
		7	$F(2, 64) = 22.198$	<.001	.410	.757
		10	$F(2, 64) = 42.729$	<.001	.572	.891
	Mean 2.5 – 3.49	4	$F(2, 64) = 36.705$	<.001	.534	.826
		7	$F(2, 64) = 38.491$	<.001	.546	.929
		10	$F(2, 64) = 18.622$	<.001	.368	.901
	Mean 3.5 – 4.0	4	$F(2, 64) = 5.497$	.001	.147	.821
		7	$F(2, 64) = 1.701$	.20	.050	.821
		10	$F(2, 64) = 4.258$	.033	.117	.696

The interaction between the number of choices and the stimulus mean rating is illustrated in Figure 5. All response sets yielded increasing functions; as the stimulus mean category increased, the mean rating increased, a result to be both expected and desired. It is notable that all three levels of response choices yielded similar patterns across the mean categories. The effect sizes across the mean differences were calculated for 4, 7, and 10 choices and these data are presented in Table 6. Note that large effect sizes were obtained across all comparisions within each response category.

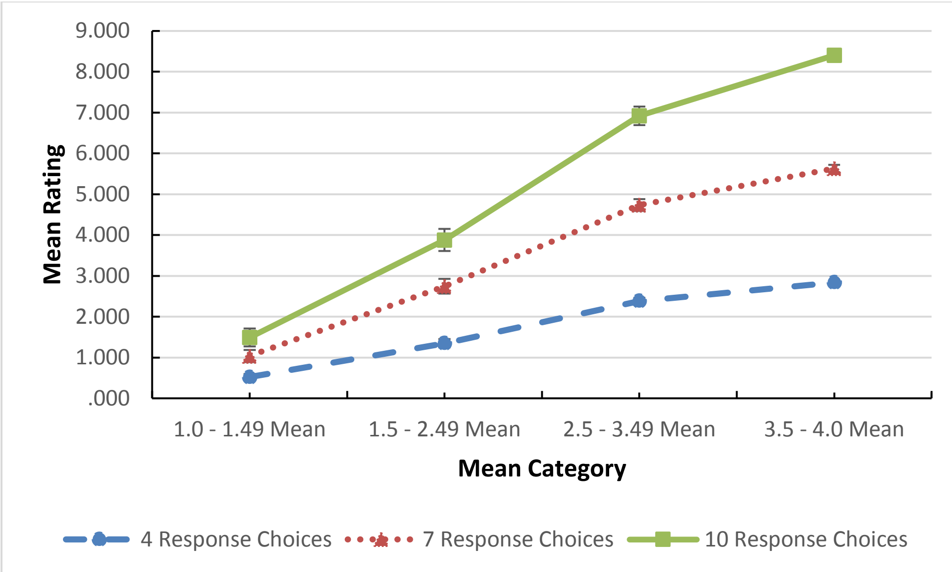


Figure 5. Mean Participant Rating as a Function of Stimulus Mean Rating

Note: Error bars are standard errors.

Table 6. ***Effect sizes across mean differences by number of response choices***

Stimulus Mean Comparison	Cohen's d 4 choices	Cohen's d 7 choices	Cohen's d 10 choices
1.0 – 1.49 to 1.5 – 2.49	1.823	2.023	1.869
1.0 – 1.49 to 2.5 – 3.49	4.106	4.386	4.253
1.0 – 1.49 to 3.5 – 4.0	5.108	5.445	5.413
1.5 – 2.49 to 2.5 – 3.49	1.804	1.925	1.965
1.5 – 2.49 to 3.5 – 4.0	2.596	2.787	2.920
2.5 – 3.49 to 3.5 – 4.0	-0.980	1.071	1.131

The interaction between the number of choices and the stimulus variablity is shown in Figure 6. Again, we observe similar patterns across all three response conditions (4, 7, and 10). It does not appear that increasing the number of response categories results in an increase in sensitivity to the manipulation of the standard deviation of the stimuli.

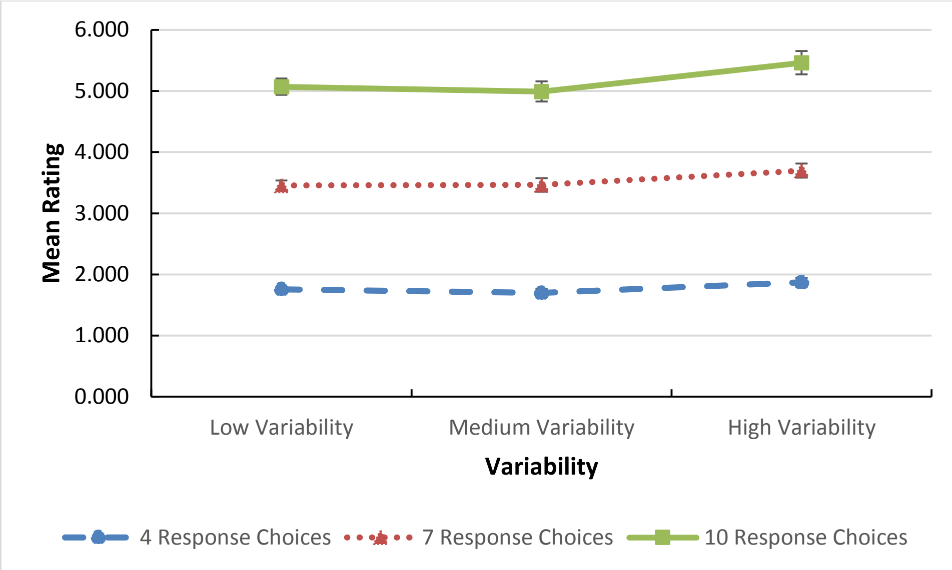


Figure 6. Mean Participant Rating as a Function of Stimulus Variability

Note: Error bars are standard errors.

Figure 7, Figure 8, and Figure 9 depict the interaction between stimulus mean category rating and stimulus variability across the three sets of response choices. Once again, a similar pattern was observed across response set conditions. Regardless of whether participants were provided response sets of 4, 7, or 10 choices, the mean ratings increased as the categories increased with similar functional patterns across variability conditions. For example, perusal of the Figures reveals that the low variabilty condition produced a similar jump between the 1.5 – 2.49 Mean and the 2.5 – 2.49 Mean across all response sets.

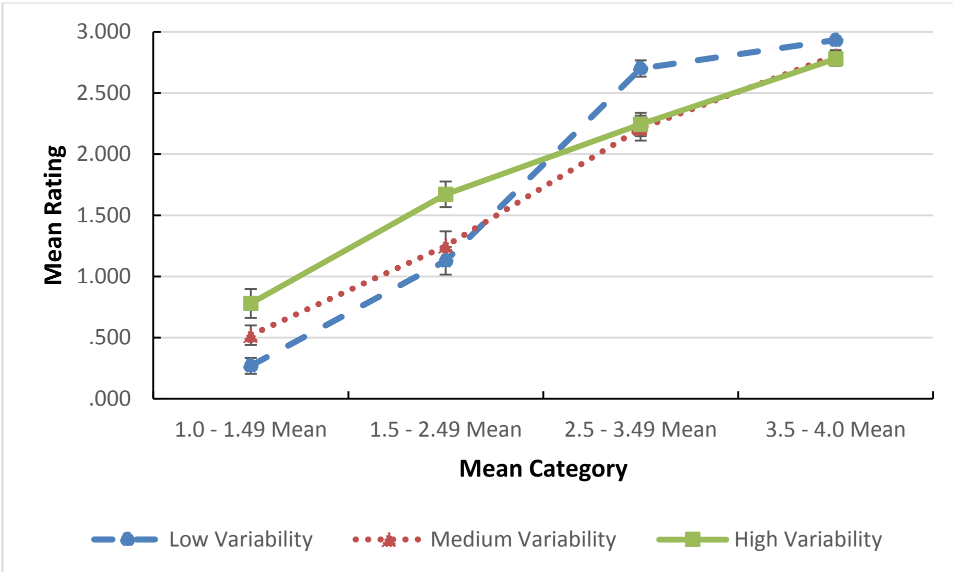


Figure 7. Mean Participant Rating as a Function of Stimulus Mean Rating for 4 Response Choices

Note: Error bars are standard errors.

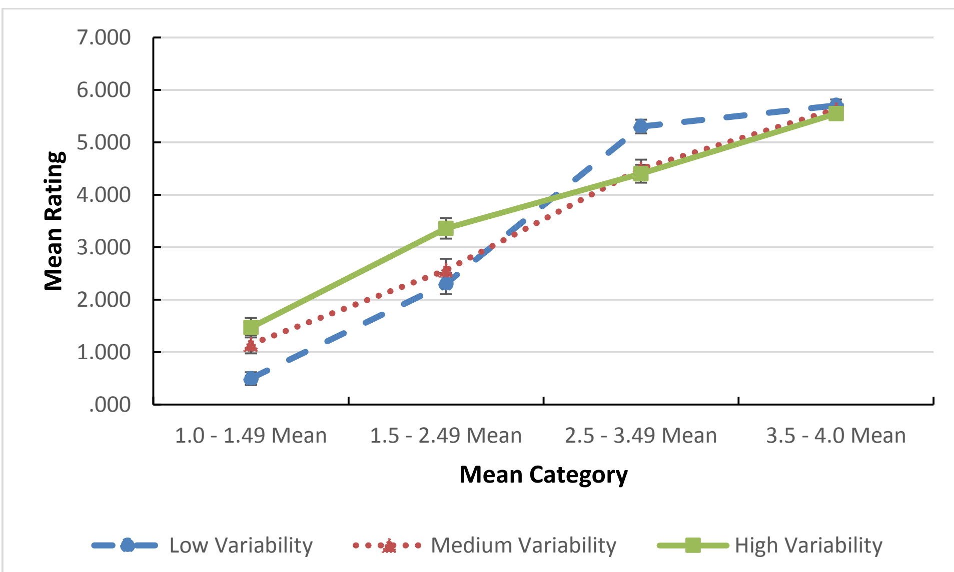


Figure 8. Mean Participant Rating as a Function of Stimulus Mean Rating for 7 Response Choices

Note: Error bars are standard errors.

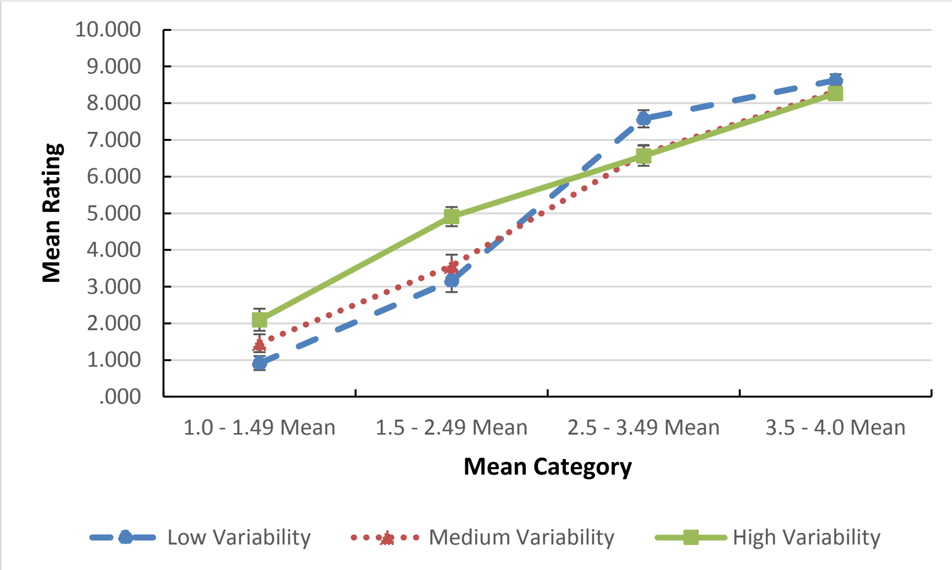


Figure 9. Mean Participant Rating as a Function of Stimulus Mean Rating for 10 Response Choices

Note: Error bars are standard errors.

Effect sizes were calculated within each response set size across the stimulus mean and stimulus variability conditions. These data are presented in Table 7. What is notable here is that although the pattern is similar across all response sizes, a few differences emerge. In the 4 response choices condition, there were larger effect sizes for larger stimulus mean ratings and for larger stimulus variability. Additionally, as the stimulus mean increased, the effect sizes changed sign across all categories. This indicates that at the lower stimulus mean categories, low variation images tend to be associated with a *lower* participant mean rating but at the higher stimulus mean categories, low variation images tend to have a *higher* partipant mean rating; that is, low variation images in the lower stimulus mean categories tend to be rated as a lower threat than more variable images and low variation images in the higher stimulus mean categories tend to be rated as a higher threat than more variable images. It was anticipated that this pattern would be replicated in subsequent experiments.

Table 7. ***Effect sizes by response choices across means and standard deviations***

Stimulus Mean	Variability compared	Cohen's d 4 choices	Cohen's d 7 choices	Cohen's d 10 choices
1.0 – 1.49	Low to Medium	0.676	0.933	0.497
	Low to High	1.382	1.386	1.077
	Medium to High	0.568	0.320	0.454
1.5 – 2.49	Low to Medium	0.186	0.223	0.225
	Low to High	0.830	0.898	0.990
	Medium to High	1.714	0.648	0.762
2.5 – 3.49	Low to Medium	-1.273	-1.068	-0.699
	Low to High	-1.194	-1.194	-0.738
	Medium to High	0.052	-0.095	-0.038
3.5 – 4.0	Low to Medium	-0.769	-0.117	-0.316
	Low to High	-0.931	-0.246	-0.372
	Medium to High	-0.108	-0.163	-0.050

Discussion

Based on the analysis, it was concluded that four response categories capture sufficient variability in ratings, as reflected in the magnitude of the effect sizes for the experimental manipulations, when participants were provided 4 response choices. The patterns across the means and standard deviations are similar to those of the 7 and 10 response choice conditions, but the effect sizes are comparable or larger in the 4 response choice set. For example, looking at a mean stimulus rating of 1.5 – 2.9 in Table 5, we see that the effect size comparing medium and high variability is much larger given a response set of 4 choices (1.714) than given a response set of 7 choices (0.648) or 10 choices (0.762). A similar increase in effect size occurs in comparing low to medium variability when the mean is 2.5 – 3.49 and again when the mean is 3.5 – 4.0. Across all conditions, we see substantial effect sizes, so we obtain meaningful differences across mean categories and variability conditions regardless of response set size. Further, the interaction between mean category and variability condition is present across all three response sets. One might expect that increasing the number of response choices would result in capturing more variability, but the empirical evidence does not indicate that this is the case for the present stimuli. Although the effect sizes are strong across all three response set conditions, we appear to gain little by increasing the response set size for participants. The response set size of 4 was therefore retained for the subsequent studies. Note that this was also the response set used in the previous studies that established the mean categories for the stimuli to be used in experiments 1 and 2.

CHAPTER 5: STUDY 1

Methods

Participants. Because of the use of structural equation modeling in this research, a direct power analysis was not performed, as too many arbitrary estimates were required. Instead, charts relating power and sample size were referenced (G. R. Hancock and Freeman, 2001) but recommended sample sizes were beyond the scope of the present work. To obtain a more tractable sample size, Kline (2011) recommends a minimum ratio for the number of participants to the number of parameters, based on the article of Jackson (2003). Using this minimum recommendation, a minimum sample size of 190 established. A total of 206 undergraduates (135 female, 71 male) at the University of Central Florida participated in the study, ranging in age from 18 to 58 (M = 20.36, SD = 4.549). Participants were recruited from undergraduate psychology courses through the SONA system, where they earned course credit for their participation. The SONA system was used to screen all participants as having normal or corrected-to-normal vision. All participants completed a brief demographic questionnaire (see Appendix B).

Experimental Design. Experiment 1 utilized a 3 (stimulus variability: low, medium, high) x 4 (stimulus mean rating: 1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0) within subjects design. Here, the stimulus rating level varied between 1 and 4 with 1 indicating that no threat was present and 4 indicating that a threat was definitely present. The dependent variable was the threat level (fuzzy membership response category) of the stimulus.

Materials. A total of 96 photographs of components (or distractors) of mock IEDs in a typical office building environment were used. The stimuli were previously normed in terms of their Fuzzy membership category using mean ratings of 242 undergraduate students at the

University of Central Florida (see previous study in chapter 3). The photographs to be used were randomly selected representatives of both mean category rating, and standard deviation within that category as divided by three roughly equal intervals. Within each of four mean categories, eight photographs of low standard deviation, eight photographs of medium standard deviation, and eight photographs of high standard deviation were used. Each of those groups (containing the eight photographs) were further partitioned, prior to random selection of the photographs, by the z-scores of the standard deviations from the mean standard deviation within the group in such a way that two photos with z-scores below -0.5, four photos with z-scores between -0.5 and 0.5, and two photos with z-scores above 0.5 were selected (see Table 8).

Table 8. Categories of Variability for Selected Photographs

	$z < -0.5$	$-0.5 < z < 0.5$	$0.5 < z$
Low Variability	2 photographs	4 photographs	2 photographs
Medium Variability	2 photographs	4 photographs	2 photographs
High Variability	2 photographs	4 photographs	2 photographs

Stimuli were presented to the participants on a standard desktop computer. A visual coding system (see Figure 12) was used to represent the response keys on the keyboard: "no threat" was color coded with green (fuzzy response category 1), "unlikely threat" was color coded with yellow (fuzzy response category 2), "likely threat" was color coded with orange (fuzzy response category 3), and "definite threat" was color coded with red (fuzzy response category 4). In addition to the color-coding with green, yellow, orange, and red, the keys also displayed the number of their rating (the green key had a 1 on it, the yellow key had a 2 on it, and so on).

Measures. Subtests of the Kit of Factor-Referenced Cognitive Tests (Ekstrom, 1976) were used to measure spatial orientation and visualization, and 50 item domain scale (10 items per domain factor) from the International Personality Item Pool (IPIP; Goldberg et al., 2006) was used to measure personality traits.

Procedure. Participants were asked to complete an informed consent and a brief demographic form. Participants then completed the tests from the Kit of Factor-Referenced Cognitive Tests and the IPIP (using pen and paper for the cognitive tests and a computerized version for the IPIP). Participants then viewed several computer screens of instructions describing the task. In these instructions, participants were told that they would be viewing images of a building that needs to be scanned for IEDs (see Figure 10 for example IEDs that were used). The participants received the explanation that an uninhabited remote vehicle has been sent into the building to take photographs of rooms, and they were viewing these photographs on a computer monitor (see Figure 11 for example stimuli) for 1600 ms each. They were instructed to respond to each image with a rating between 1 and 4, where 1 indicates that the room is free of threats and 4 indicates the room definitely contains a threat. Participants received instructions that the colors on the response keys on the keyboard represent the different potential threat levels of the rooms.

Participants were then given an example of the fuzzy ratings using a non-IED stimulus. Photographs of a model ship in different stages of assembly were shown to the participants, and they were told what rating the experimenter would assign to the photograph along with a brief explanation of the properties of the stimulus that indicate the rating is appropriate. The detailed instructions are provided in the Appendix A. Following the instructions, participants were asked if they have any questions regarding the task or the rating system.

Participants then viewed the pre-selected stimuli on a computer monitor for a duration of 1600 milliseconds. Following the stimulus, a screen requesting a rating was presented and the participant could not advance to the next trial until a rating had been entered. The presentation of the stimuli was blocked so that images of low variability across all mean categories appear in one block, images of medium variability appear in a second block, and images of high variability appear in a third block. Each block was separated by a masking screen, so that the participants' ratings of individual pictures should not be influenced by the variability associated with the preceding picture. The order of mean category block was randomized within each variability condition. The order of variability block presentation was counter-balanced: six configurations of the three blocks were possible, and each participant was randomly assigned to one of those six conditions. The presentation order of the pictures within each block was predetermined by randomizing the sequence.

At the conclusion of the experiment, participants were debriefed.

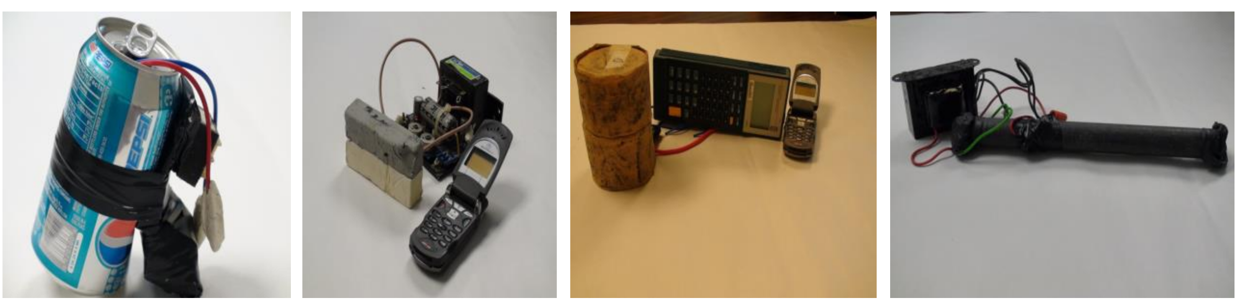


Figure 10: Types of IEDs.

Figure 11: Example stimuli.

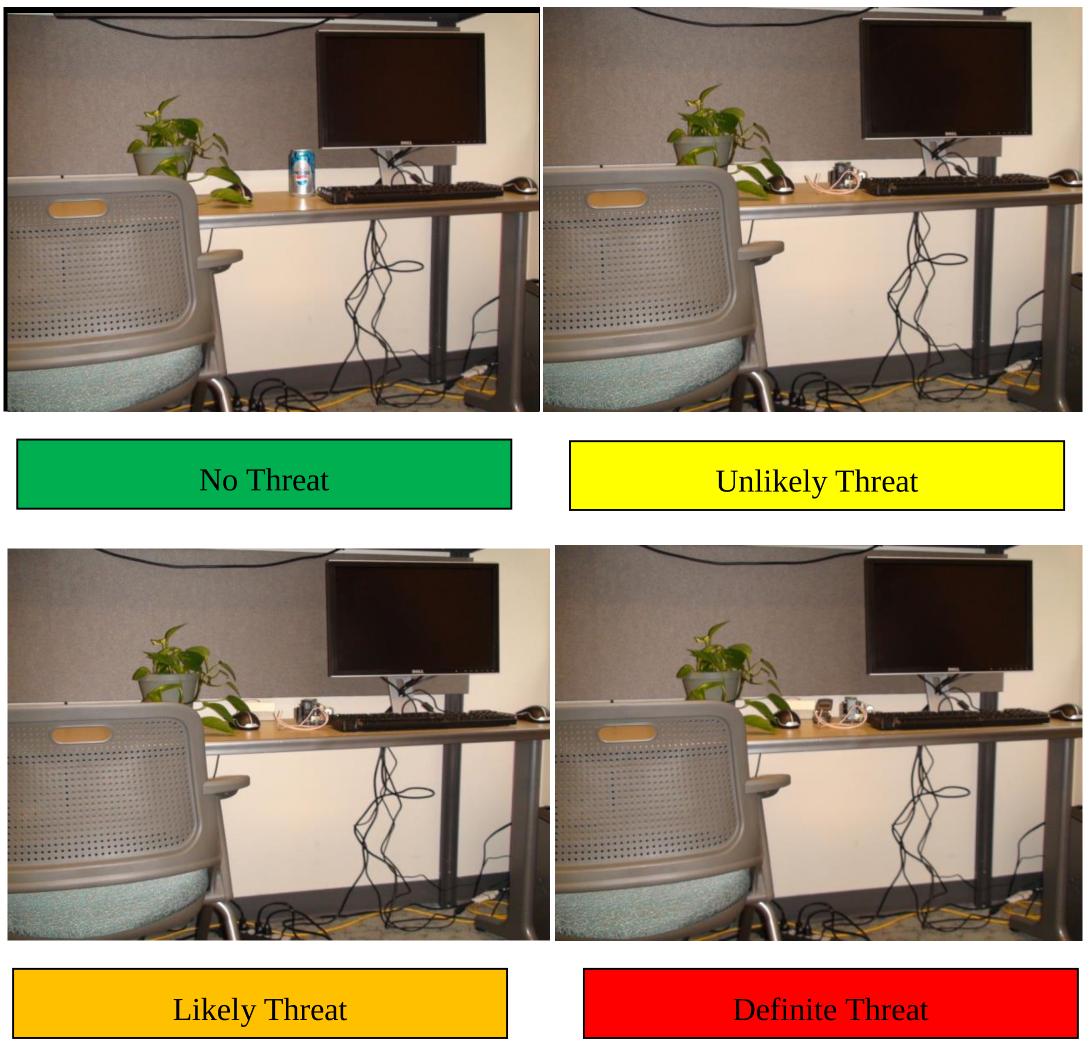


Figure 12: Visual Coding System.

Results

Mapping Functions. Each stimulus in the study had a mean rating that fell into one of four categories: low (1.0 – 1.49); medium low (1.5 – 2.49); medium high (2.5 – 3.49); or high (3.5 – 4). These categorical values defined the state of the world for this study, and a mapping function is necessary to assign a fuzzy signal strength to each stimulus. Initially, an equal interval linear mapping function that assigned fuzzy signal strength based on stimulus category mapping was explored; that is, all pictures with mean ratings from 1.0 – 1.49 were assigned a fuzzy signal strength of 0, all pictures with mean ratings from 1.5 – 2.49 were assigned a fuzzy signal strength of 1/3, all pictures with mean ratings from 2.5 – 3.49 were assigned a fuzzy signal strength of 2/3, and all pictures with mean ratings from 3.5 – 4 were assigned a fuzzy signal strength of 1. However, it was apparent that a great deal of information was lost with such a mapping. Using this strategy, fuzzy estimates could not be obtained for the low and high categories, as these contained no degree of hit or no degree of miss.

Thus, degree of signal was defined for each picture using the mapping

$$s = \frac{picture\ mean - 1.11}{2.79}$$

where 1.11 is the minimum stimulus mean and 2.79 is the range of stimulus means. Thus, the picture with the lowest stimulus mean was mapped to $s = 0$ and the picture with the highest stimulus mean was mapped to $s = 1$. An equal interval linear mapping was used for the response: a response of low was mapped to $r = 0$; a response of medium low was mapped to $r = 1/3$; a response of medium high was mapped to $r = 2/3$; and a response of high was mapped to $r = 1$.

Preliminary Analysis. In analyzing the data, Greenhouse-Geisser was used to correct for violation of sphericity in most F tests involved; where appropriate, the uncorrected degrees of freedom are reported as well as the epsilon used for the correction. The means and standard deviations of participant rating responses and participant median response times are provided in Table 9 and Table 10.

Table 9. ***Descriptive Statistics for Participant Rating Responses (N=206)***

Stimulus Mean	Stimulus Variability	Response Mean	Response Standard Deviation
1.0 – 1.49	Low	1.2364	.32569
	Medium	1.4033	.41047
	High	1.6474	.56065
1.5 – 2.49	Low	2.1011	.60825
	Medium	2.2223	.56672
	High	2.5284	.53652
2.5 – 3.49	Low	3.5041	.38909
	Medium	2.9547	.47618
	High	3.0130	.53693
3.5 – 4.0	Low	3.8642	.20585
	Medium	3.6387	.32154
	High	3.7027	.27813

Table 10. ***Descriptive Statistics for Participant Response Times (N=206)***

Stimulus Mean	Stimulus Variability	Response Mean	Response Standard Deviation
1.0 – 1.49	Low	542.6796	324.82168
	Medium	637.1553	467.01625
	High	698.0801	493.81265
1.5 – 2.49	Low	800.5534	562.79445
	Medium	798.4369	649.87026
	High	765.1820	513.00128
2.5 – 3.49	Low	552.7840	341.94345
	Medium	666.8010	385.79495
	High	691.5340	469.64025
3.5 – 4.0	Low	460.5801	270.74238
	Medium	539.5194	285.37100
	High	494.5583	273.50497

Participant responses were analyzed with a two-way analysis of variance having four levels of stimulus mean rating (1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0) and three levels of stimulus variability (low, medium, high). All main effects and interactions were statistically significant at the .05 significance level (see Table 11). Pairwise comparisons showed significant differences between each mean category and significant differences between each variability category.

Table 11. 4x3 ANOVA of Participant Responses

Effect	*df*	*ε*	*SS*	*MS*	*F*	*p*	η_p^2
Stimulus Mean	3	.772	1890.906	630.302	2996.658	<.001	.936
Error	615		129.356	.210			
Stimulus Variability	2	.966	12.421	6.210	40.973	<.001	.167
Error	410		62.144	.152			
Stimulus Mean*Stimulus Variability	6	.800	68.245	11.374	147.471	<.001	.418
Error	1230		94.868	.077			

Additional one-way ANOVAs were computed to further investigate the interactions. Tests of the effects of mean category at each level of signal variability indicated statistically significant main effects for stimulus mean at low stimulus variability, $F(3, 615) = 2549.425$, $p < .001$, $\varepsilon = .763$, $\eta_p^2 = .926$, at medium stimulus variability, $F(3, 615) = 1712.750$, $p < .001$, $\varepsilon = .875$, $\eta_p^2 = .893$, and at high stimulus variability, $F(3, 615) = 1162.175$, $p < .001$, $\varepsilon = .935$, $\eta_p^2 = .850$. At low stimulus variability, there was a significant linear trend, $F(1, 205) = 7851.697$, $p < .001$, $\eta_p^2 = .975$, quadratic trend, $F(1, 205) = 122.692$, $p < .001$, $\eta_p^2 = .374$, and cubic trend, $F(1, 205) = 179.312$, $p < .001$, $\eta_p^2 = .467$. At medium stimulus variability, there was a significant linear trend, $F(1, 205) = 4105.893$, $p < .001$, $\eta_p^2 = .952$, and quadratic trend, $F(1, 205) = 8.607$, $p = .004$, $\eta_p^2 = .040$. At high stimulus variability, there was a significant linear trend, $F(1, 205) = 2611.664$, $p < .001$, $\eta_p^2 = .927$, quadratic trend, $F(1, 205) = 16.770$, $p < .001$, $\eta_p^2 = .076$, and cubic trend, $F(1, 205) = 33.905$, $p < .001$, $\eta_p^2 = .142$.

These interactions are depicted in Figure 13. As expected, lower variability stimuli were associated with lower responses in the lower stimulus mean categories and higher responses in the higher stimulus mean categories. Figure 13 shows that, as variability increases, ratings increase in the lower stimulus mean categories; however, there is not a similar trend in the higher stimulus mean categories.

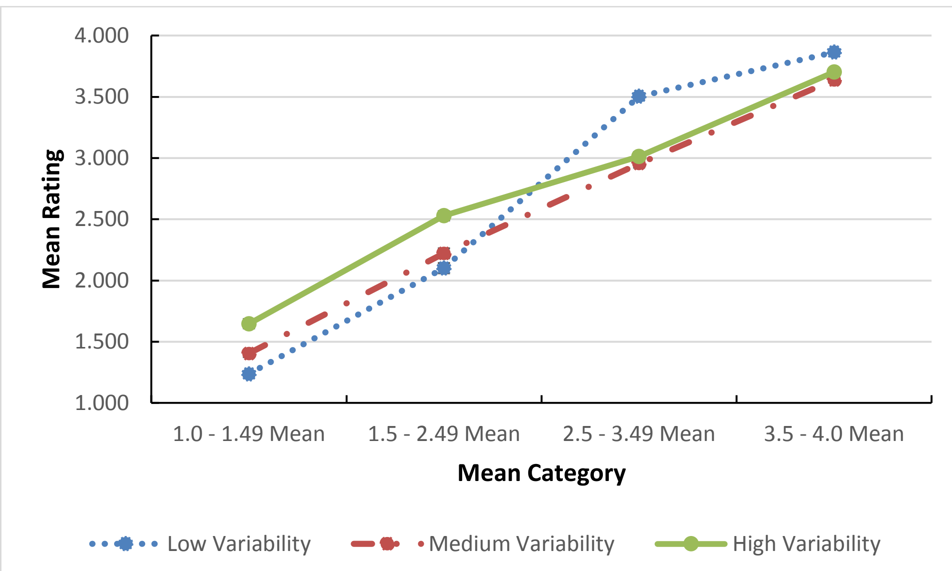


Figure 13. Mean Participant Response as a Function of Mean Stimulus Category in Study 1

Note: Error bars are standard errors

Participant median response times were analyzed with a two-way analysis of variance having four levels of stimulus mean rating (1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0) and three levels of stimulus variability (low, medium, high). All main effects and interactions were statistically significant at the .05 significance level (see Table 12).

Table 12. 4x3 ANOVA of Participant Response Times

Effect	*df*	ε	*SS*	*MS*	*F*	*p*	η_p^2
Stimulus Mean	3	.827	26079387.898	8693129.299	66.422	<.001	.245
Error	615		80489950.435	130877.968			
Stimulus Variability	2		2869702.904	1434851.452	4.188	.016	.020
Error	410		140478527.430	342630.555			
Stimulus Mean*Stimulus Variability	6	.827	2721061.163	453510.194	5.453	<.001	.026
Error	1230		102304089.504	83174.057			

Additional one-way ANOVAs were computed to further investigate the interactions. Tests for the effects of mean category at each level of signal variability indicated statistically significant main effects for stimulus mean at low stimulus variability, $F(3, 615) = 52.650$, $p < .001$, $\varepsilon = .678$, $\eta_p^2 = .204$, at medium stimulus variability, $F(3, 615) = 21.553$, $p < .001$, $\varepsilon = .780$, $\eta_p^2 = .095$, and at high stimulus variability, $F(3, 615) = 27.046$, $p < .001$, $\varepsilon = .965$, $\eta_p^2 = .117$. At low stimulus variability, there was a significant linear trend, $F(1, 205) = 44.471$, $p < .001$, $\eta_p^2 = .178$, quadratic trend, $F(3, 615) = 70.586$, $p < .001$, $\eta_p^2 = .256$, and cubic trend, $F(3, 615) = 42.003$, $p < .001$, $\eta_p^2 = .170$. At medium stimulus variability, there was a significant linear trend, $F(1, 205) = 15.339$, $p < .001$, $\eta_p^2 = .070$, quadratic trend, $F(3, 615) = 41.522$, $p < .001$, $\eta_p^2 = .168$, and cubic trend, $F(3, 615) = 8.836$, $p = .003$, $\eta_p^2 = .041$. At high stimulus variability, there was a significant linear trend, $F(1, 205) = 46.333$, $p < .001$, $\eta_p^2 = .184$, and quadratic trend, $F(3, 615) = 33.124$, $p < .001$, $\eta_p^2 = .139$.

Figure 14 shows the pattern of response time across conditions. Across all levels of variability, there is an increase in response time at the middle low stimulus mean category, and the fastest response time occurring in the high stimulus mean category. Except in the middle low stimulus mean category, low variability pictures yield faster response times.

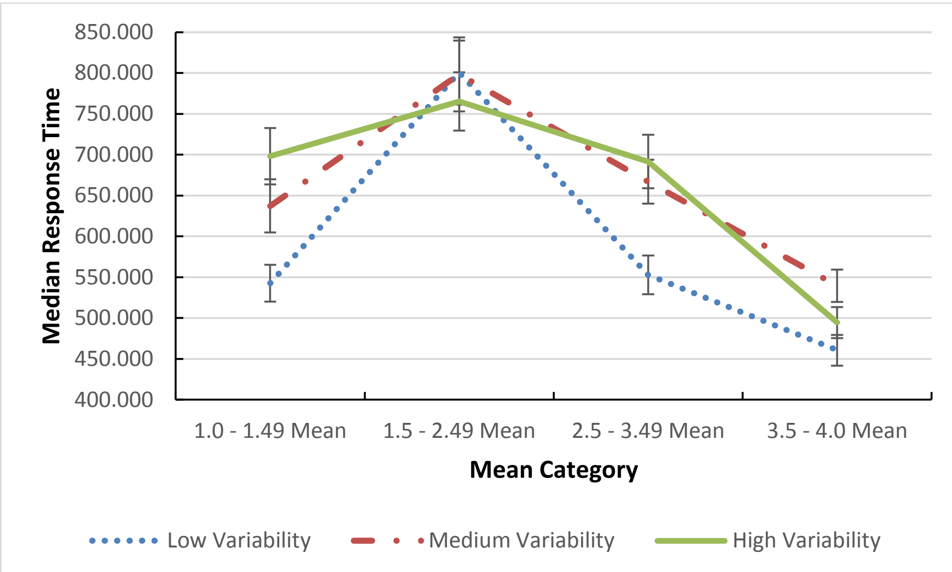


Figure 14. Mean Participant Response Time as a Function of Stimulus Mean Category in Study 1

Note: Error bars are standard errors.

Personality and Cognitive Traits. All cognitive tests penalized for incorrect answers; thus, negative scores were possible. A perfect score on the ETS Card Rotation Test (S1) is 160 and the lowest score possible is -160; a perfect score on the ETS Cube Comparison Test (S2) is 42 and the lowest score possible is -42; a perfect score on the ETS Form Board Test (VZ1) is 48 and the lowest score possible is -48; a perfect score on the ETS Paper Folding Test (VZ2) is 20 and the lowest possible score is -20; and a perfect score on the ETS Surface Development Test (VZ3) is 60 and the lowest possible score is -60. For the 50 item version of the International Personality Item Pool (IPIP), each factor has a max score of 50. The means and standard deviations of participants' performance on the cognitive tests and personality factors are shown in Table 13.

Table 13. ***Descriptive Statistics for Cognitve and Personality Tests (N=206)***

Trait	Mean	Standard Deviation
S1	93.75	35.847
S2	13.33	10.504
VZ1	2.35	16.250
VZ2	5.37	6.838
VZ3	16.78	24.220
Extraversion	31.76	8.736
Emotional Stability	30.94	8.031
Conscientiousness	35.58	6.476
Agreeableness	39.99	6.215
Intellect/Imagination	36.83	5.927

Correlations. Correlations were run between the five cognitive tests (spatial ability: S1—ETS Card Rotation Test, S2—ETS Cube Comparison Test; visualization ability: VZ1—ETS Form Board Test, VZ2—ETS Paper Folding Test, VZ3—ETS Surface Development Test), average sensitivity (d'), average response bias (c), and median average response time (RT). These correlations were run with the data collapsed over all signal variability categories. All correlations were significant, except response time only had a significant correlation with S1 (see Table 14).

Table 14. ***Correlations of Cognitive Traits with SDT Measures***

	Correlation Coefficients							
	S1	S2	VZ1	VZ2	VZ3	d'	C	RT
S1	1							
S2	.515**	1						
VZ1	.425**	.609**	1					
VZ2	.402**	.562**	.641**	1				
VZ3	.481**	.656**	.713**	.694**	1			
d'	.245**	.264**	.294**	.288**	.335**	1		
C	.259**	.257**	.255**	.243**	.266**	.366**	1	
RT	-.236**	-.078	.022	.027	.035	.104	-.010	1

$^{**}p \leq .01$

Correlations were also computed between the personality characteristics (extraversion, emotional stability, and conscientiousness), average sensitivity, average response bias, and median average response time. These correlations were also computed with the data collapsed over all signal variability categories. Table 15 shows that extraversion correlated with both sensitivity and response time, such that higher extraversion scores were associated with lower sensitivity and longer response time. Emotional stability also correlated positively with response time.

Table 15. Correlation of Personality Traits with SDT Measures

	Correlation Coefficients					
	Extraversion	Emotional Stability	Conscientiousness	d'	c	RT
Extraversion	1					
Emotional Stability	.188**	1				
Conscientiousness	.170*	.191**	1			
d'	-.165*	-.025	.038	1		
C	-.030	.067	.036	.366**	1	
RT	-.191**	.146*	.088	.104	-.010	1

$*p \leq .05$, $**p \leq .01$

Sensitivity. Sensitivity was analyzed with a two-way analysis of variance having three levels of stimulus variability (low, medium, high) and four levels of stimulus mean rating (1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0). All main effects and interactions were statistically significant at the .05 significance level, with η_p^2 values in the medium-to-large range (see Table 16).

Table 16. 3 (Stimulus Variability) x4 (Stimulus Mean Category) ANOVA of Sensitivity

Effect	*df*	*ε*	*SS*	*MS*	*F*	*p*	η_p^2
Stimulus Variability	2		14.154	7.077	29.827	<.001	.127
Error	410		97.280	.237			
Stimulus Mean	3	.891	81.322	27.107	89.896	<.001	.305
Error	615		185.449	.302			
Stimulus Variability *Stimulus Mean	6	.899	48.186	8.031	48.590	<.001	.192
Error	1230		203.295	.165			

The interaction between the stimulus variability and the stimulus mean category is illustrated in Figure 15. As seen in the figure, both medium and high variability pictures resulted in greater values of d' for the middle stimulus mean categories. The pictures of low variability, however, showed a decline between the two middle categories, rising again for the highest mean category to approximately the same value as the lowest mean category. Both the lowest mean category and the highest mean category have decreasing values of d' across increasing variability of the stimulus, whereas the middle two mean categories both peak for medium variability pictures.

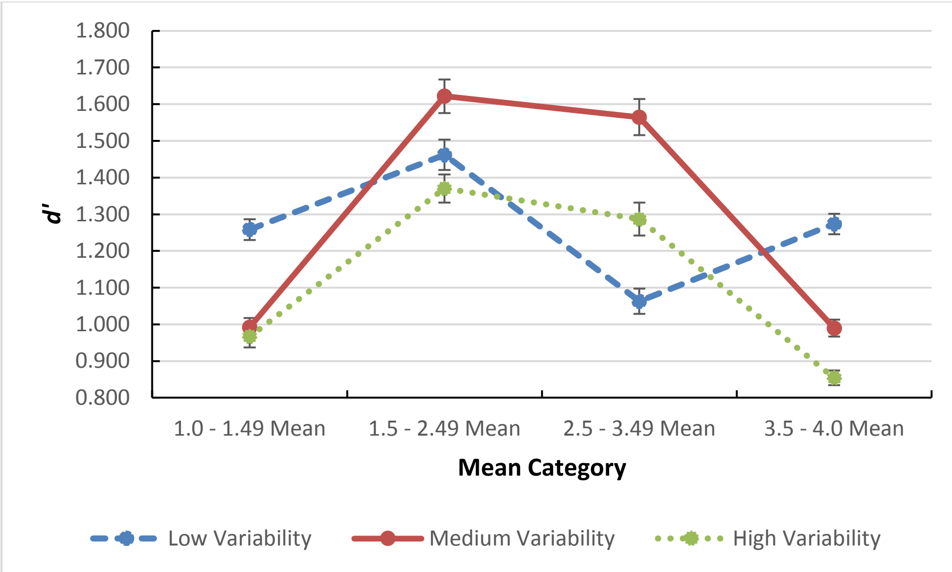


Figure 15. Mean Sensitivity as a Function of Stimulus Mean Category in Study 1

Note: Error bars are standard errors.

Additional one-way ANOVAs of mean category within each level of variability were computed to further investigate the interactions. Tests of the effect of mean category at each level of signal variability indicated significant main effects for stimulus mean at low stimulus variability, $F(3, 615) = 26.417$, $p < .001$, $\varepsilon = .935$, $\eta_p^2 = .114$, at medium stimulus variability, $F(3, 615) = 104.319$, $p < .001$, $\varepsilon = .874$, $\eta_p^2 = .337$, and at high stimulus variability, $F(3, 615) = 68.509$, $p < .001$, $\varepsilon = .911$, $\eta_p^2 = .250$. At low variability, there was a significant linear trend, $F(1, 205) = 8.062$, $p = .005$, $\eta_p^2 = .038$, and cubic trend, $F(1, 205) = 73.801$, $p < .001$, $\eta_p^2 = .265$. At medium variability, there was a significant quadratic trend, $F(1, 205) = 254.063$, $p < .001$, $\eta_p^2 = .553$. At high variability, there was a significant linear trend, $F(1, 205) = 13.918$, $p < .001$, $\eta_p^2 = .064$, and quadratic trend, $F(1, 205) = 157.379$, $p < .001$, $\eta_p^2 = .434$.

Response Bias. Response bias was analyzed with a two-way analysis of variance having three levels of stimulus variability (low, medium, high) and four levels of stimulus mean rating

(1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0). All main effects and interactions were statistically significant at the .05 significance level (see Table 17).

Table 17. 3 (Stimulus Variability) x4 (Stimulus Mean Category) ANOVA of Response Bias

Effect	*df*	*ε*	*SS*	*MS*	*F*	*P*	η_p^2
Stimulus Variability	2		11.503	5.752	26.552	<.001	.115
Error	410		88.812	.217			
Stimulus Mean	3	.840	830.922	276.974	906.174	<.001	.816
Error	615		187.976	.306			
Stimulus Variability *Stimulus Mean	6	.885	32.099	5.350	40.905	<.001	.164
Error	1230		164.116	.133			

Figure 16 shows the interaction between stimulus mean category and stimulus variability. As the mean category increases, response bias decreases across all levels of stimulus variability. Thus, there is an inclination towards responding signal absent for the lowest level of stimulus mean category (1.0 – 1.49 mean), little bias present at the next lowest level of stimulus mean (1.5 – 2.49 mean), and a tendency to respond signal present at the higher levels of stimulus mean. Note that signals of lower variability are slightly more inclined to ilicit a stronger response bias at the medium high stimlulus mean category level (2.5 – 3.49 mean) than the other variability levels.

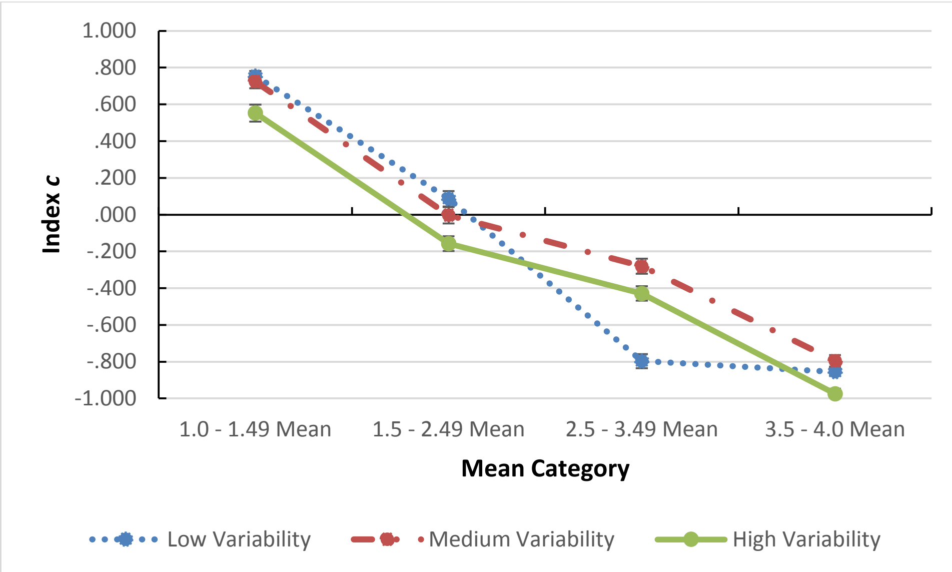


Figure 16. Mean Response Bias as a Function of Stimulus Mean Category in Study 1

Note: Error bars are standard errors.

Tests of the effect of mean category at each level of variability were computed to further investigate the interactions. The ANOVAs showed significant main effects for stimulus mean at low stimulus variability, $F(3, 615) = 640.479$, $p < .001$, $\varepsilon = .923$, $\eta_p^2 = .758$, at medium stimulus variability, $F(3, 615) = 440.641$, $p < .001$, $\varepsilon = .932$, $\eta_p^2 = .682$, and at high stimulus variability, $F(3, 615) = 426.962$, $p < .001$, $\varepsilon = .857$, $\eta_p^2 = .676$. At low variability, there was a significant linear trend, $F(1, 205) = 2184.355$, $p < .001$, $\eta_p^2 = .914$, quadratic trend, $F(1, 205) = 99.065$, $p < .001$, $\eta_p^2 = .326$, and cubic trend, $F(1, 205) = 49.673$, $p < .001$, $\eta_p^2 = .195$. At medium variability, there was a significant linear trend, $F(1, 205) = 1002.519$, $p < .001$, $\eta_p^2 = .830$, quadratic trend, $F(1, 205) = 12.612$, $p < .001$, $\eta_p^2 = .058$, and cubic trend, $F(1, 205) = 34.937$, $p < .001$, $\eta_p^2 = .146$. At high variability, there was a significant linear trend, $F(1, 205) = 807.754$, $p < .001$, $\eta_p^2 = .798$, quadratic trend, $F(1, 205) = 9.052$, $p = .003$, $\eta_p^2 = .042$, and cubic trend, $F(1, 205) = 40.265$, $p < .001$, $\eta_p^2 = .164$.

Structural Equation Modeling with Cognitive Factors. The results shown in Table 14 indicated strong correlations between the cognitive measures implemented (two spatial tests, S1 and S2, and three visualization tests, VZ1, VZ2, and VZ3). Consequently, one model grouping these together as the common factor "cognitive skills" was developed (see Figure 17), and a reasonable model fit was obtained (CFI = 1.000; TLI ρ^2 = 1.016; RMSEA < .001, 90% CI (< .001, .029); AIC = 22.846; $\chi^2(4)$ = .846, p = .932). As seen in the model, the latent factor accounts for large portions of the observed variance.

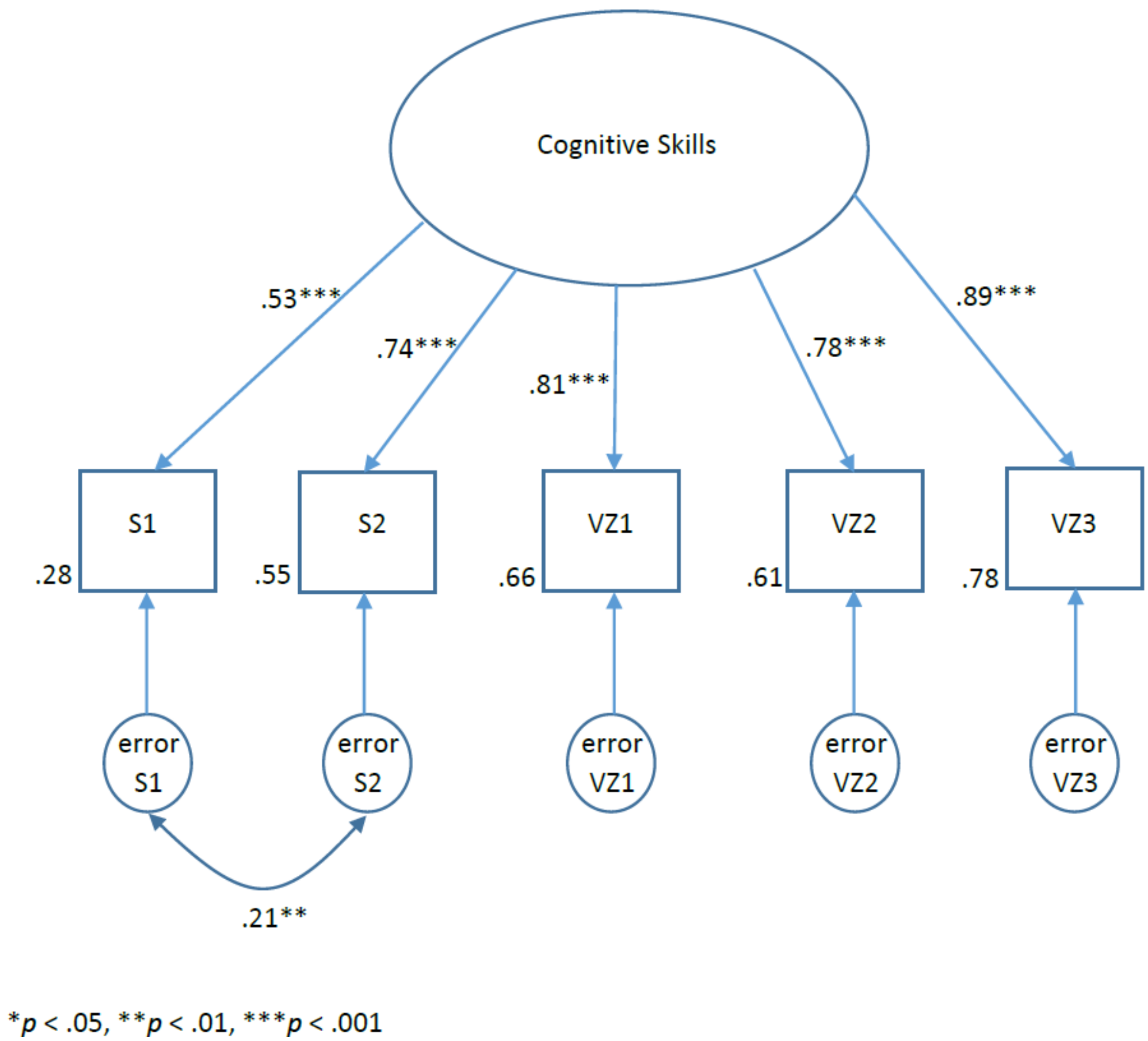


Figure 17. Model 1: SEM Model of Single Cognitive Factor

Note: Standardized path coefficients shown. R^2 values are indicated next to each observed variable. Observed variables not shown.

Model 1 groups all cognitive skills into one latent factor. A second latent structure was tested in which the cognitive skills were grouped by two factors: spatial ability and visualization ability. The basic structure provided a reasonable fit (CFI = 1.000; TLI ρ^2 = 1.016; RMSEA < .001, 90% CI (< .001, .029); AIC = 22.846; $\chi^2(4)$ = .846, p = .932). However, the two factor model resulted in a poor fit when incorporated into a structural regression model for response time (CFI = .908; TLI ρ^2 = .849; RMSEA = .088, 90% CI (.074, .103); AIC = 354.763; $\chi^2(83)$ = 214.763, p < .001) and for sensitivity (CFI = .844; TLI ρ^2 = .790; RMSEA = .078, 90% CI (.064, .091); AIC = 330.427; $\chi^2(101)$ = 226.427, p < .001), although an adequate fit was observed for response bias (CFI = .988; TLI ρ^2 = .982; RMSEA = .031, 90% CI (< .001, .051); AIC = 232.628; $\chi^2(91)$ = 108.628, p = .100). As a result, the latent structure of Model 1 was used to analyze the relation of the cognitive traits to performance.

A structural regression model (Model 2) was developed to analyze sensitivity as a function of the latent variable specified in Model 1. Model 2 also proved to have a reasonable fit (CFI = .970; TLI ρ^2 = .960; RMSEA = .034, 90% CI (< .001, .052); AIC = 228.779; $\chi^2(101)$ = 124.779, p = .054). Figure 18, depicts the structure of Model 2.

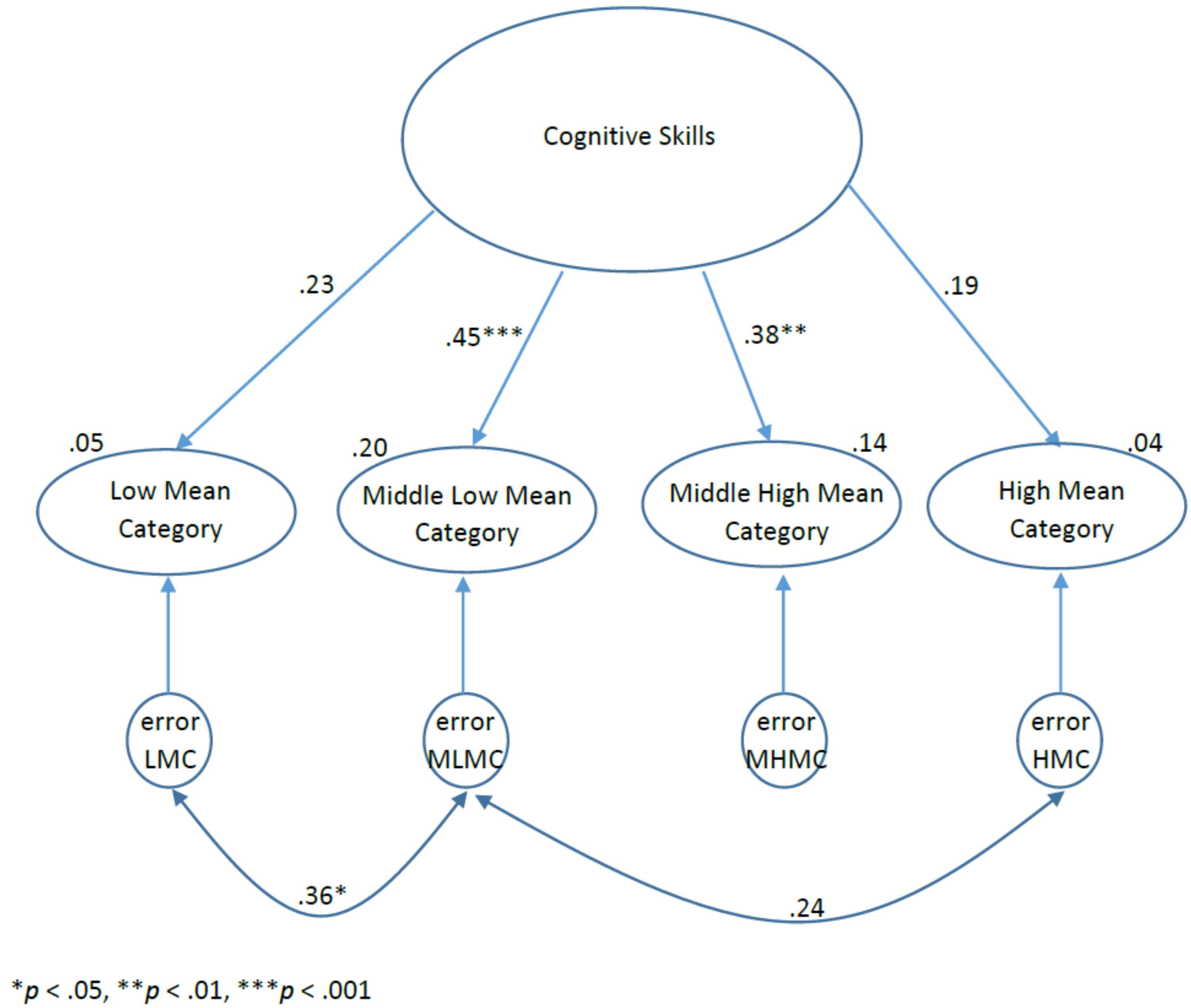


Figure 18. Model 2: Latent Structure of SEM Model Analyzing *d'*

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables not shown.

As seen in the model, Cognitive Skills accounts for more variability in sensitivity performance across the two middle mean categories, but cognitive skills were not strongly associated with performance in the two extreme category conditions. Thus, the cognitive traits predict sensitivity in the conditions in which the stimulus category membership is more ambiguous.

Model 3 analyzed variation in response bias as a function of the cognitive skills factor of Model 1. Model 3 also has a reasonable fit (CFI = .991; TLI ρ^2 = .985; RMSEA = .028, 90% CI (< .001, .049); AIC = 234.449; $\chi^2(85) = 98.449$, p = .151). Figure 19, depicts the structure of Model 3.

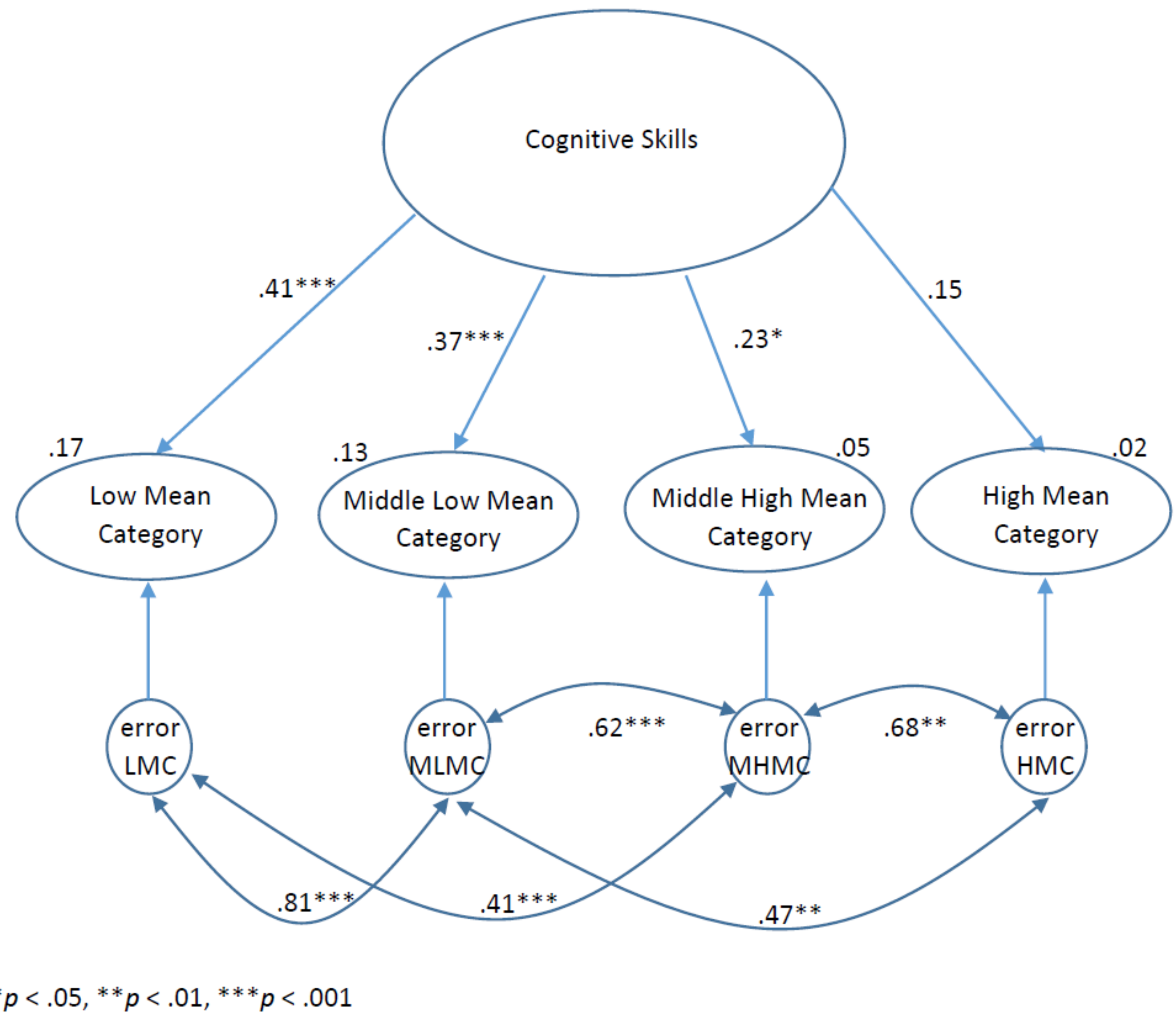


Figure 19. Model 3: Latent Structure of SEM Model Analyzing Index c

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables not shown.

Cognitive Skills accounts for more variability in criterion setting in the low mean categories compared to the high mean categories. Higher cognitive skill was associated with greater conservatism in responding, but more so for stimuli with lower signal membership.

Model 4 analyzed variation in response time as a function of the cognitive skills factor of Model 1. Model 4 also has a reasonable fit (CFI = .976; TLI ρ^2 = .959; RMSEA = .046, 90% CI (.025, .064); AIC = 260.005; $\chi^2(81)$ = 116.005, p = .007). However, cognitive skills did not significantly predict response time across levels of mean category. Figure 20 depicts the structure of Model 4.

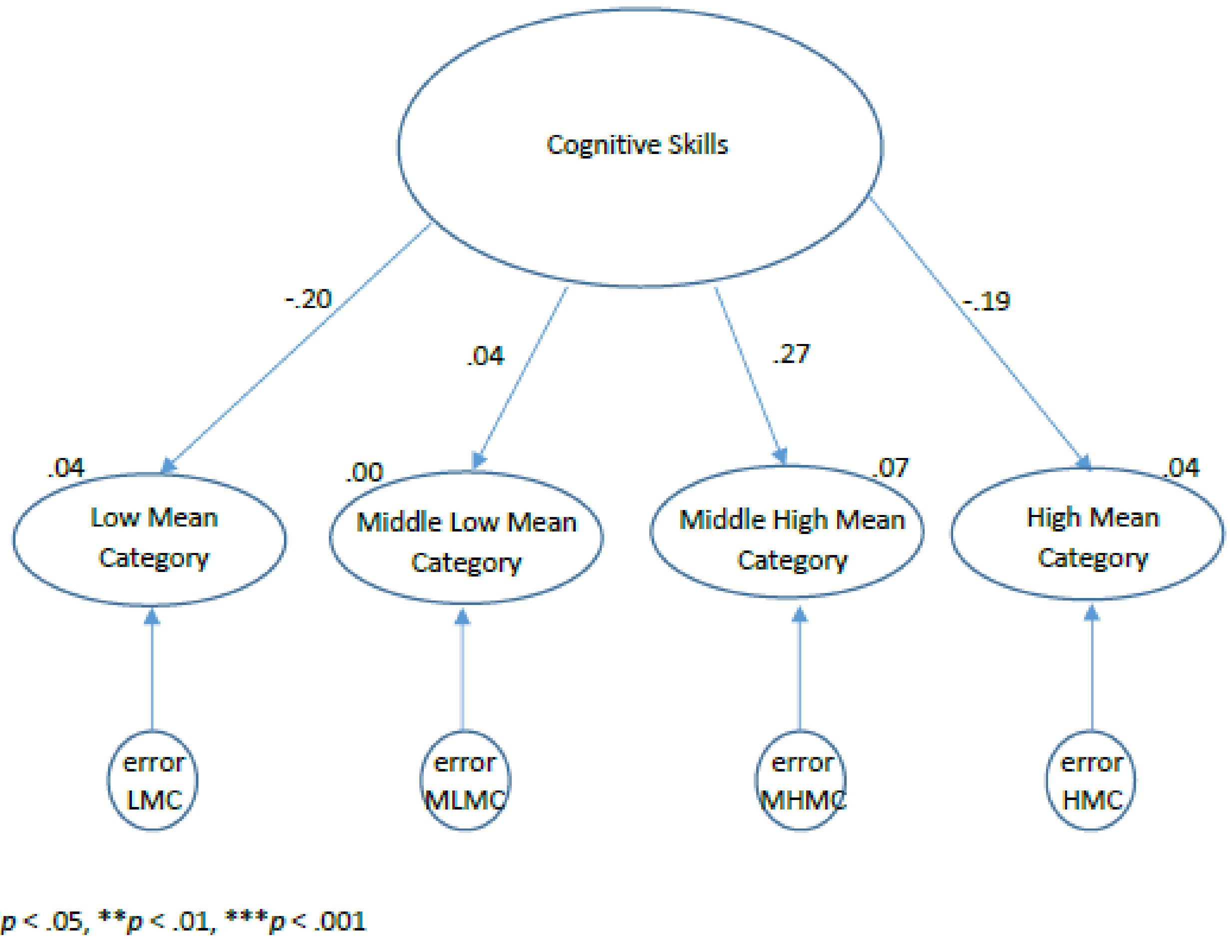


Figure 20. Model 4: Latent Structure of SEM Model Analyzing Response Time

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables not shown.

Structural Equation Modeling Incorporating Personality Traits. Structural regression analyses were conducted to analyze the effect of the three personality traits on *d'*, *c*, and response time (Models 5, 6, and 7, respectively) and a subsequent analysis illustrates the interaction between the cognitive and personality characteristics effect on these three performance criterions (Models 8, 9, and 10, respectively). Analysis of sensitivity is shown in Model 5 (see Figure 21) and a reasonable model fit was obtained (CFI = 1.000; TLI ρ^2 = 1.025; RMSEA < .001, 90% CI (< .001, .035); AIC = 170.061; $\chi^2(65) = 60.061$, $p = .650$).

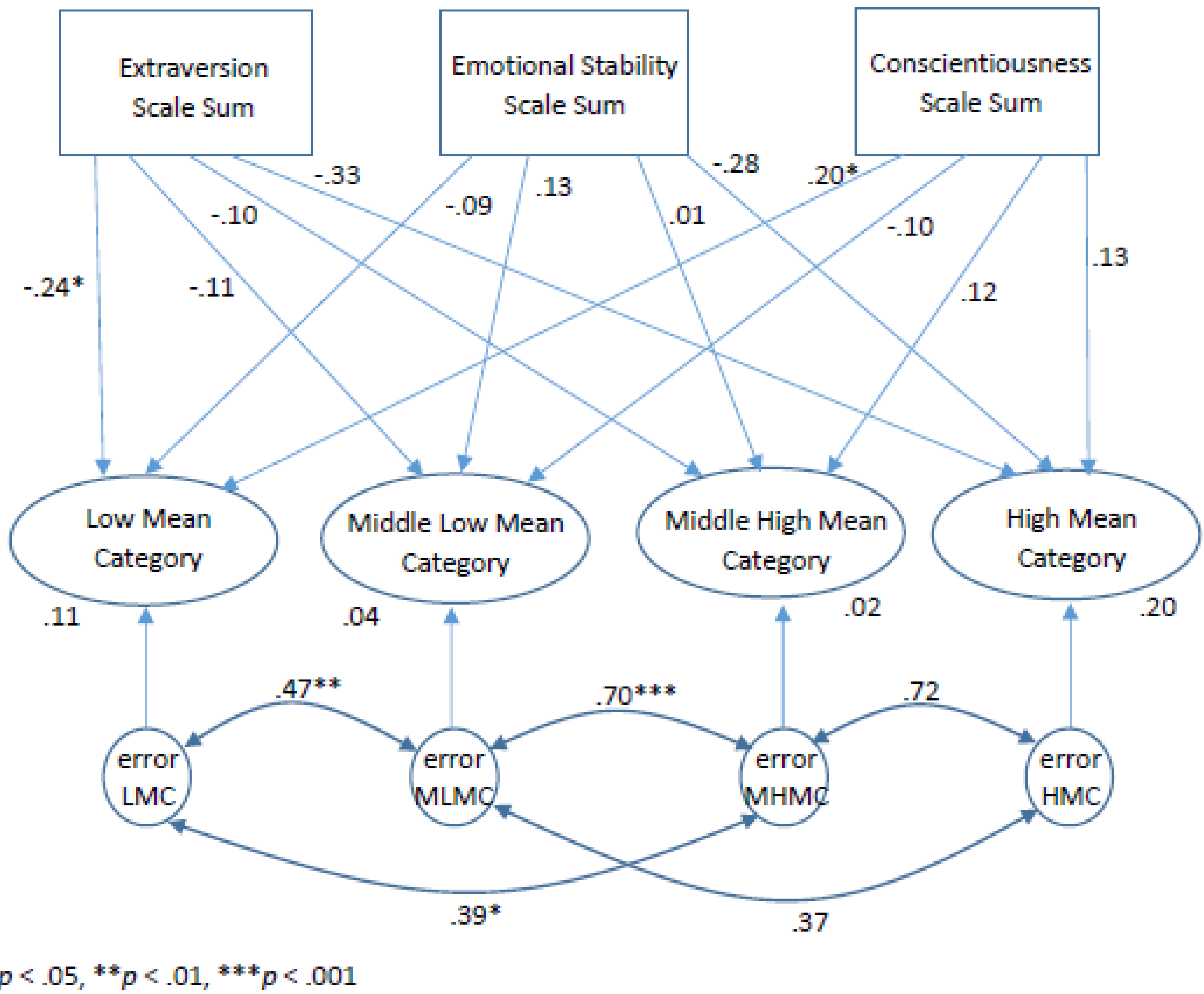


Figure 21. Model 5: SEM of Personality Traits Analyzing *d'*

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables not shown.

The personality factors account for more of the variance in the extreme stimulus mean categories, having little effect on sensitivity in the middle categories. Individuals high in conscientiousness are more discriminating than those low on the trait, but only in the low stimulus mean category. Extroverts tend to be less discriminating, but only at the lowest threat level, the low stimulus mean category.

Response bias was analyzed in Model 6 (see Figure 22). A reasonable model fit was obtained (CFI = 1.000; TLI ρ^2 = 1.002; RMSEA < .001, 90% CI (< .001, .043); AIC = 187.186; $\chi^2(52) = 51.186$, $p = .506$). However, the personality traits did not significantly predict criterion setting across levels of mean category.

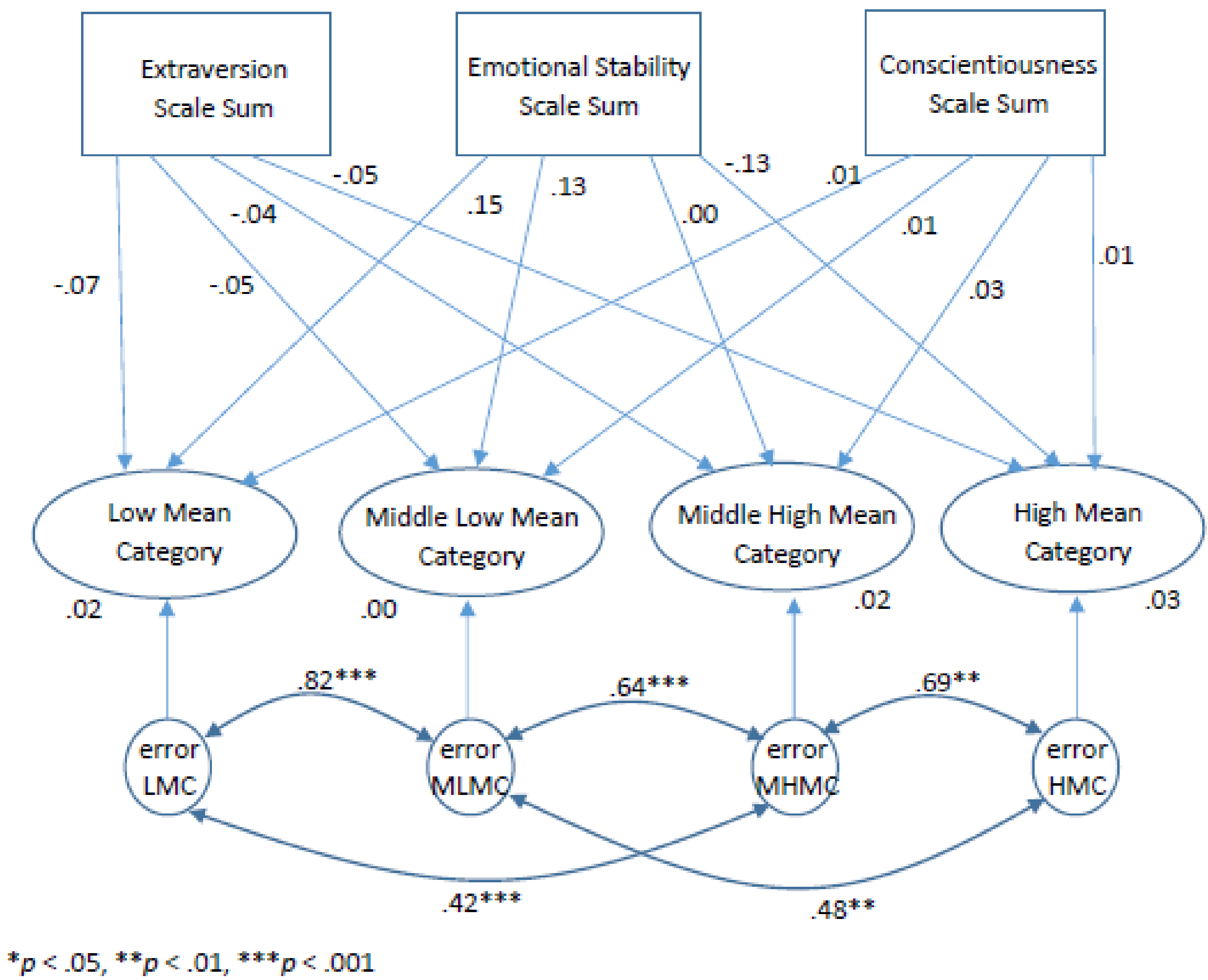
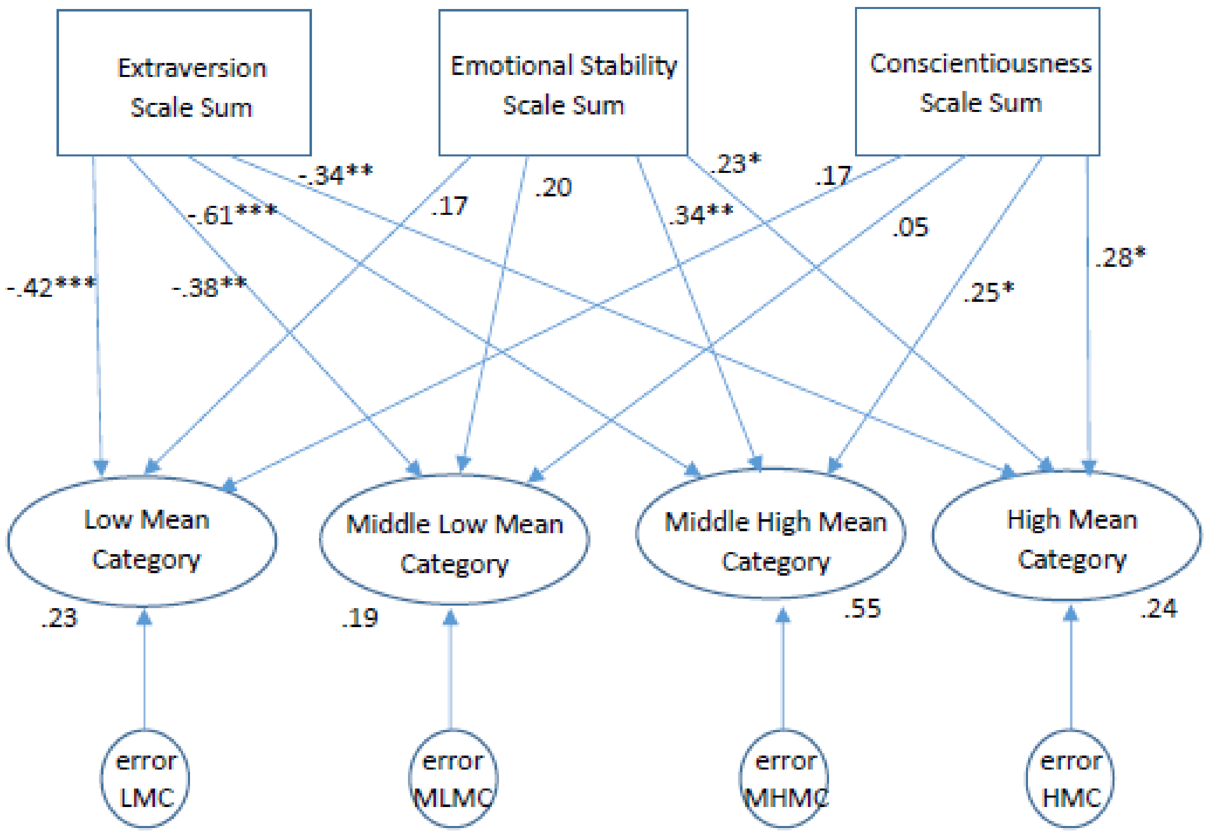


Figure 22. Model 6: SEM of Personality Traits Analyzing Index *c*

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables not shown.

Response time was analyzed in Model 7 (see Figure 23), and a reasonable model fit was obtained (CFI = .970; TLI ρ^2 = .934; RMSEA = .054, 90% CI (.030, .076); AIC = 220.797; $\chi^2(48) = 76.797$, $p = .005$).



*p < .05, **p < .01, ***p < .001

Figure 23. Model 7: SEM of Personality Traits Analyzing Response Time

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables for response time factors are not shown.

The personality factors accounted for the highest amount of variance in response time in the middle high stimulus mean category, but contributed substantially to each category. Extraverts tended to respond faster across all mean categories. Individuals high in emotional stability and conscientiousness tended to have longer response times, but these differences were significant only in the middle high and high stimulus mean categories.

Model 8 (Figure 24) illustrates the interaction between cognitive skills and extraversion on sensitivity performance. A reasonable model fit was obtained (CFI = 1.000; TLI ρ^2 = 1.109;

RMSEA < .001, 90% CI (< .001, < .001); AIC = 154.007; $\chi^2(65) = 44.007$, $p = .979$). As the model shows, however, the effect that the cognitive skills factor has on sensitivity does not depend on extraversion (i.e., the cognitive skills by extraversion interaction term was not significantly related to performance).

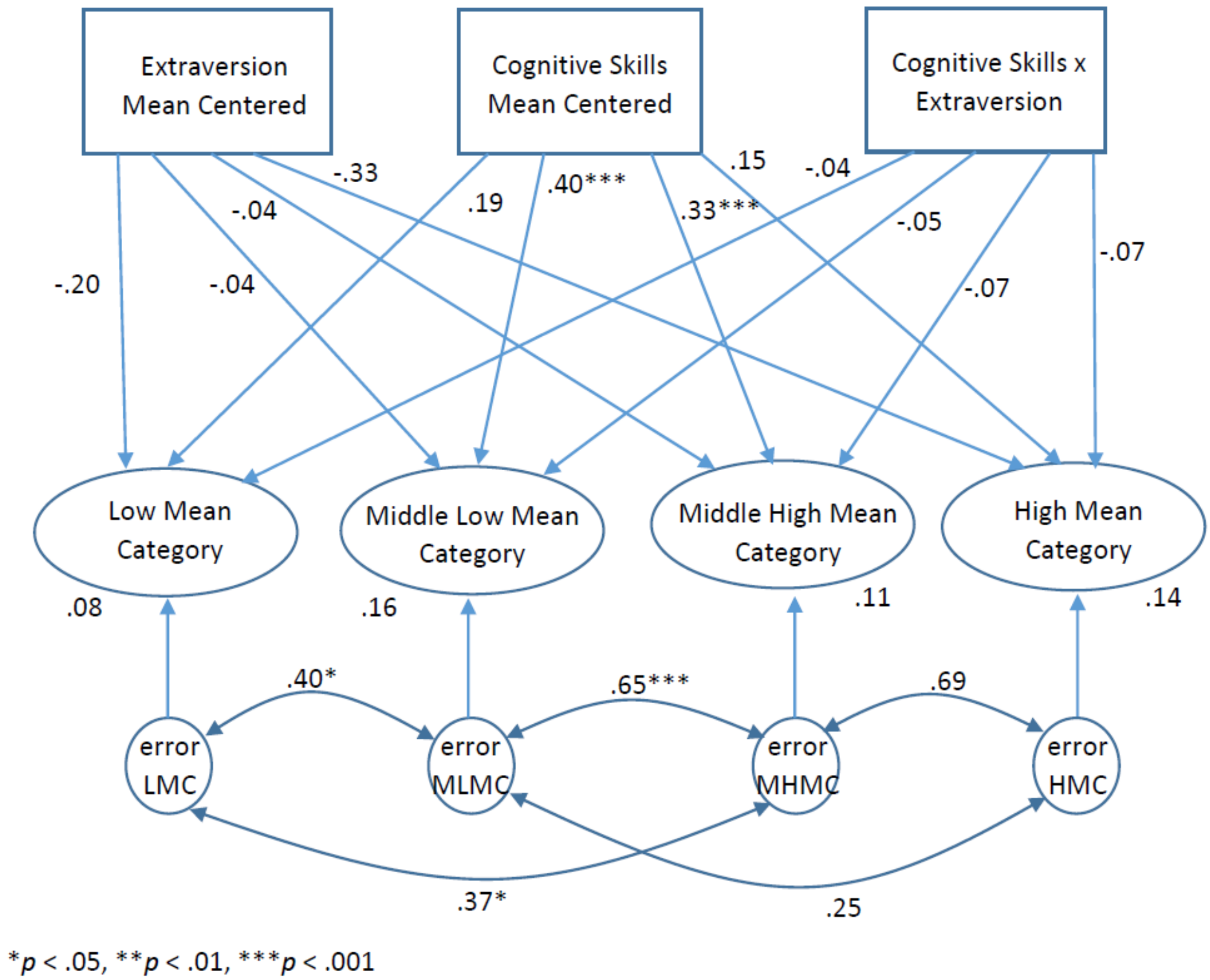


Figure 24. Model 8: SEM Analysis of Extraversion Interacting with Cognitive skills for *d'*

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables for sensitivity factors are not shown.

Model 9 (Figure 25) illustrates the interaction between cognitive skills and extraversion on response bias. A reasonable model fit was obtained (CFI = 1.000; TLI ρ^2 = 1.006; RMSEA < .001, 90% CI (< .001, .040); AIC = 185.104; $\chi^2(52)$ = 49.104, p = .588). As the model shows, however, the effect that the cognitive skills factor has on criterion setting does not depend on extraversion.

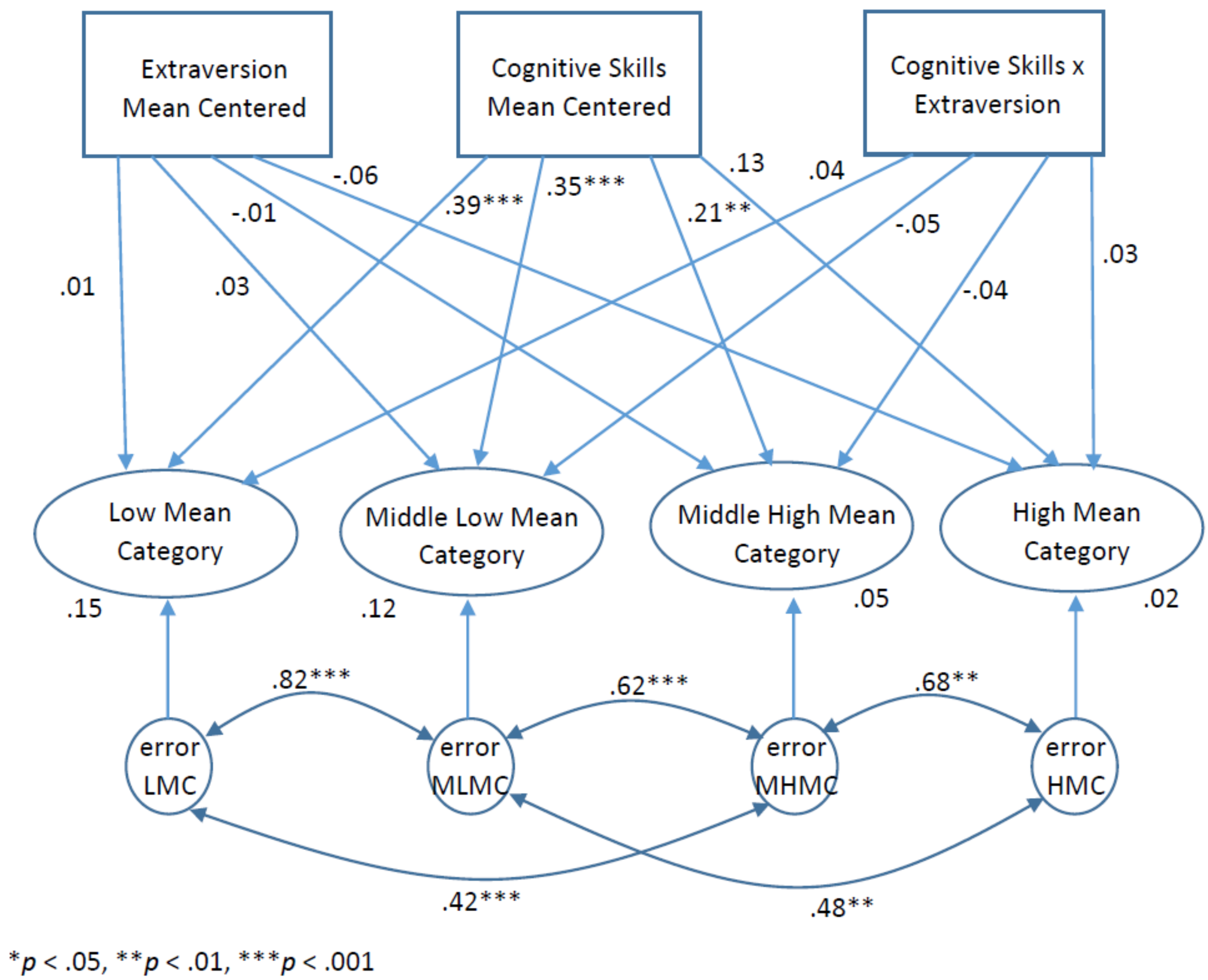
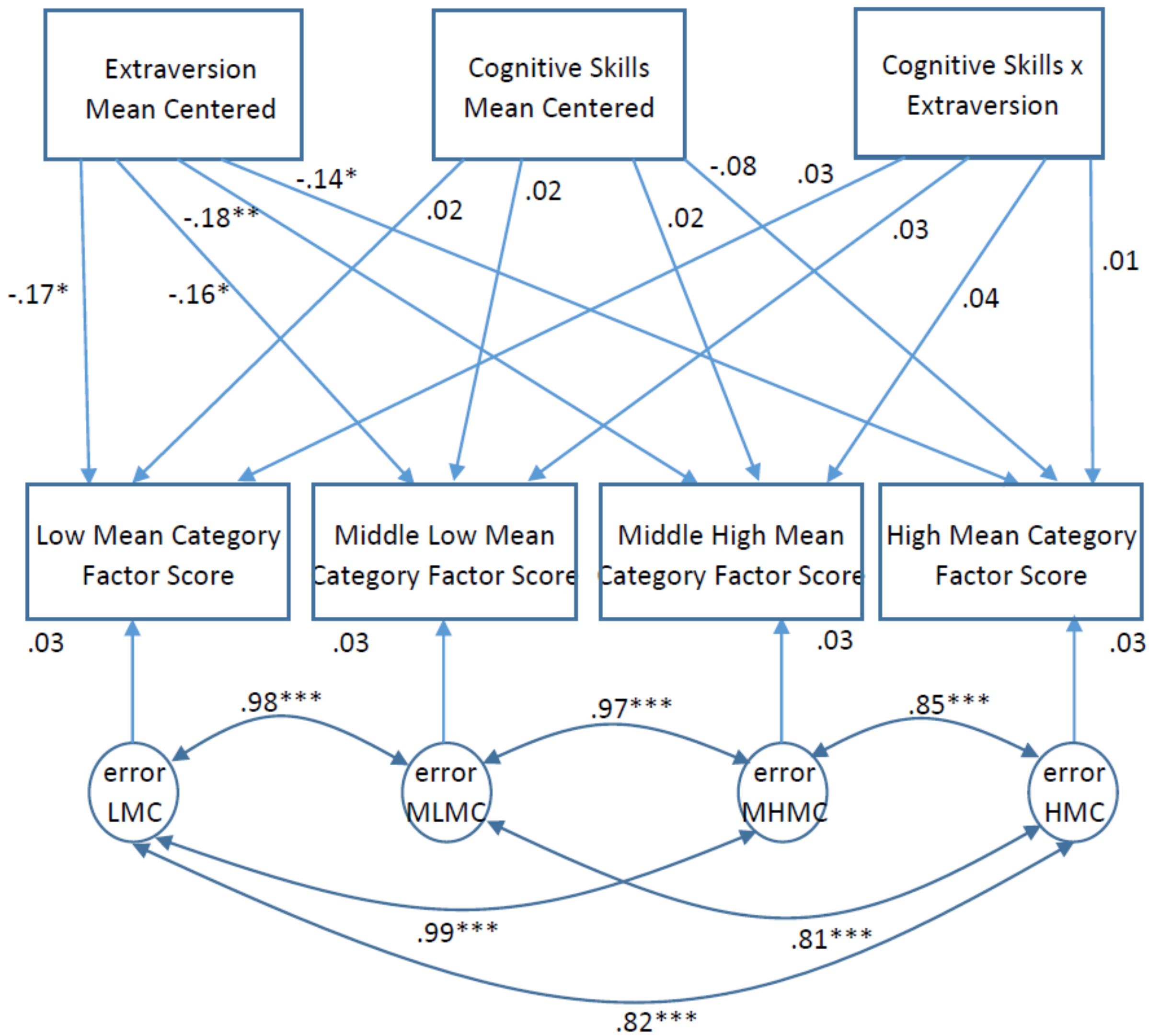


Figure 25. Model 9: SEM Model Analysis of Cognitive Skills Interacting with Extraversion for Index *c*

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables for response bias factors not shown.

Analysis of response time failed to converge to a solution using the same latent model structure as in the previous two models, so a path analysis was conducted. Model 10 (Figure 26) illustrates the interaction between cognitive skills and extraversion on response time. A reasonable model fit was obtained (CFI = 1.000; TLI ρ^2 = .997; RMSEA = .037, 90% CI (< .001, .129); AIC = 53.821; $\chi^2(3)$ = 3.821, p = .281). As the model shows, however, the effect that extraversion has on response time does not depend on the cognitive skills factor.

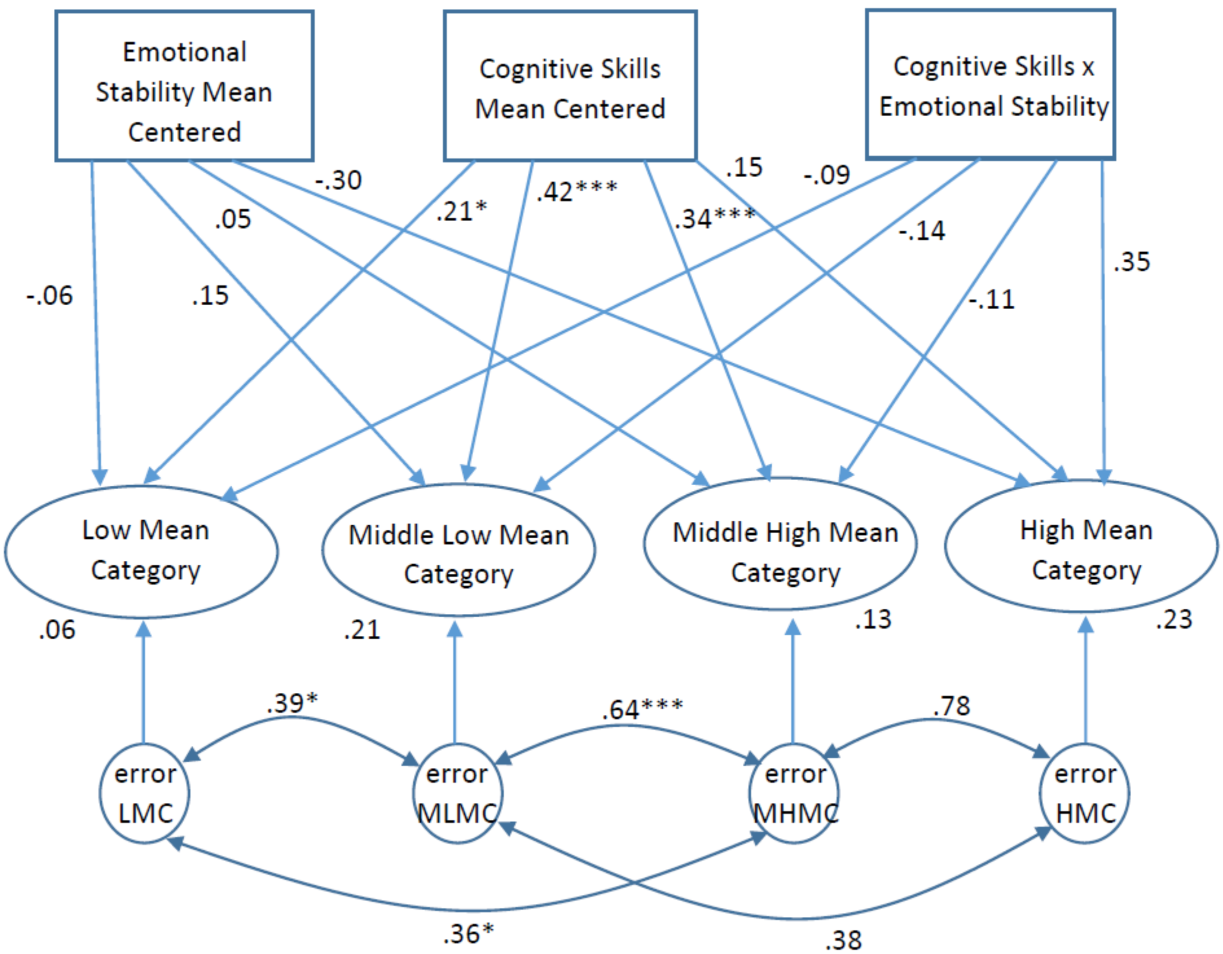


*p < .05, **p < .01, ***p < .001

Figure 26. Model 10: Path Analysis of Cognitive Skills Interacting with Extraversion for Response Time

Note: Path coefficients are standardized. R^2 values for each observed variable for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category.

Model 11 (Figure 27) illustrates the interaction between cognitive skills and emotional stability on sensitivity. A reasonable model fit was obtained (CFI = 1.000; TLI ρ^2 = 1.066; RMSEA < .001, 90% CI (< .001, .020); AIC = 161.504; $\chi^2(65)$ = 51.504, p = .888). As the model shows, however, the effect that the cognitive skills factor has on sensitivity does not depend on emotional stability.



*p < .05, **p < .01, ***p < .001

Figure 27. Model 11: SEM Analysis of Emotional Stability Interacting with Cognitive skills for *d'*

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables for sensitivity factors are not shown.

Model 12 (Figure 28) illustrates the interaction between cognitive skills and emotional stability on response bias. A reasonable model fit was obtained (CFI = .999; TLI ρ^2 = .997; RMSEA = .011, 90% CI (< .001, .046); AIC = 189.199; $\chi^2(52) = 53.199$, $p = .428$). For every increase of one unit in emotional stability the regression coefficient for the prediction of response bias by cognitive skills decreased by -0.20 (middle low mean category) and -0.15 (middle high mean category). Stated another way, higher emotional stability tended to weaken the relationship between cognitive skills and response bias, but low emotional stability was associated with a stronger relationship of cognitive skills to criterion setting.

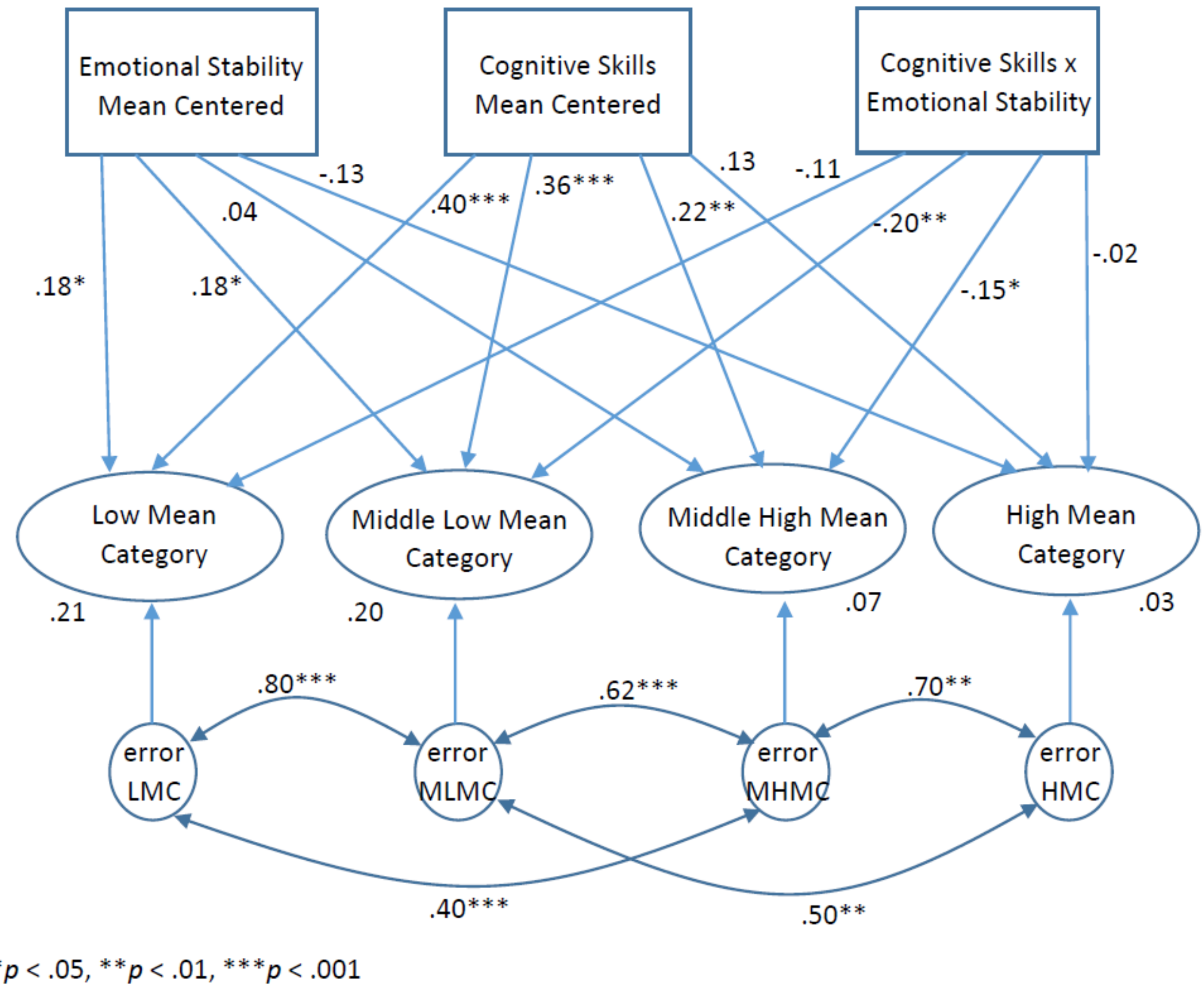
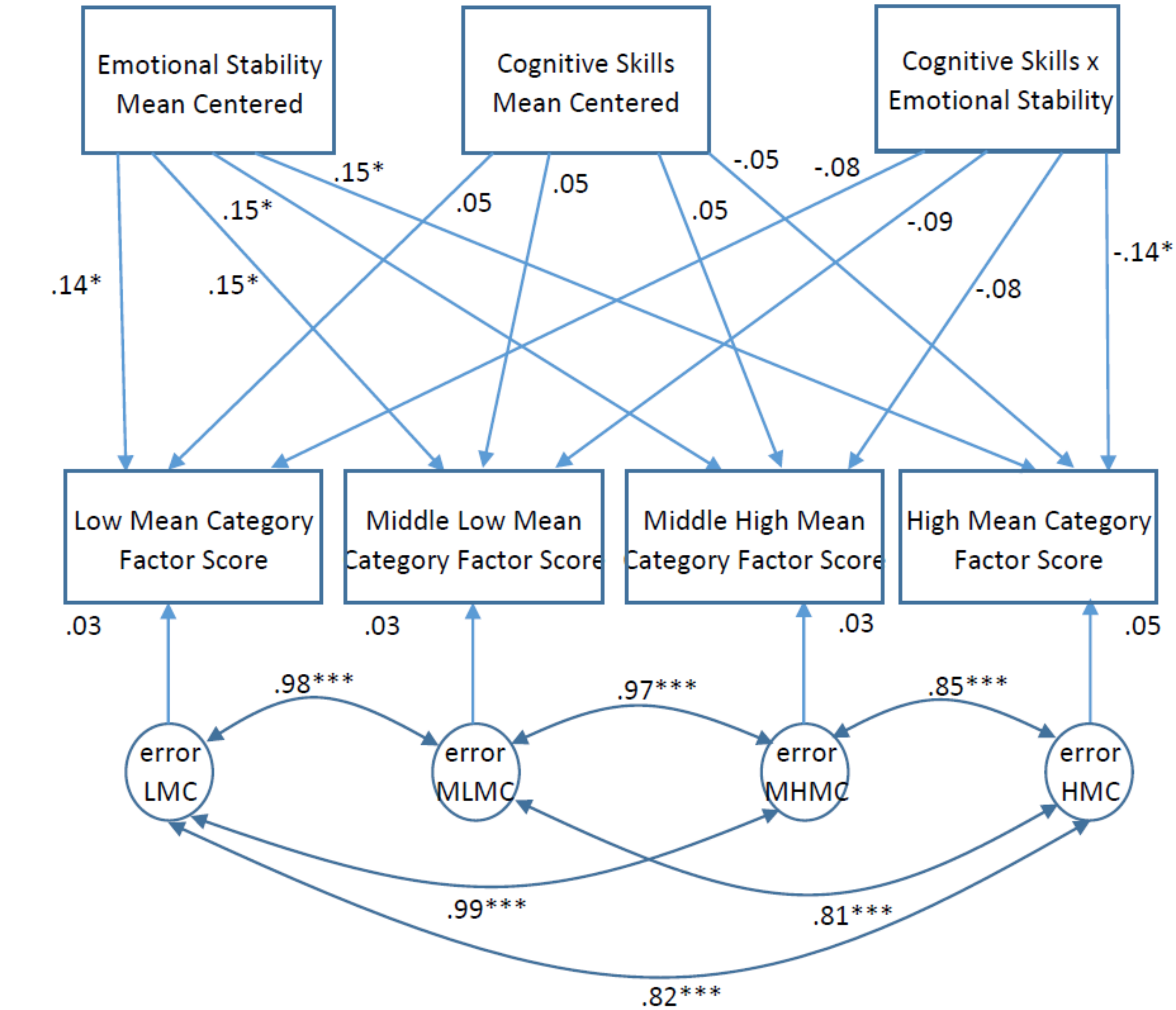


Figure 28. Model 12: SEM Analysis of Emotional Stability Interacting with Cognitive skills for Index *c*

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables for response bias factors are not shown.

Response time was again analyzed with a path analysis (Model 13). A reasonable model fit was obtained (CFI = .999; TLI ρ^2 = .992; RMSEA = .058, 90% CI (< .001, .143); AIC = 55.090; $\chi^2(3) = 5.090$, p = .165). Model 13 is depicted in Figure 29. Higher emotional stability was associated with longer response time, but for the highest mean category this relationship was stronger for those lower rather than higher on the cognitive skills factor.

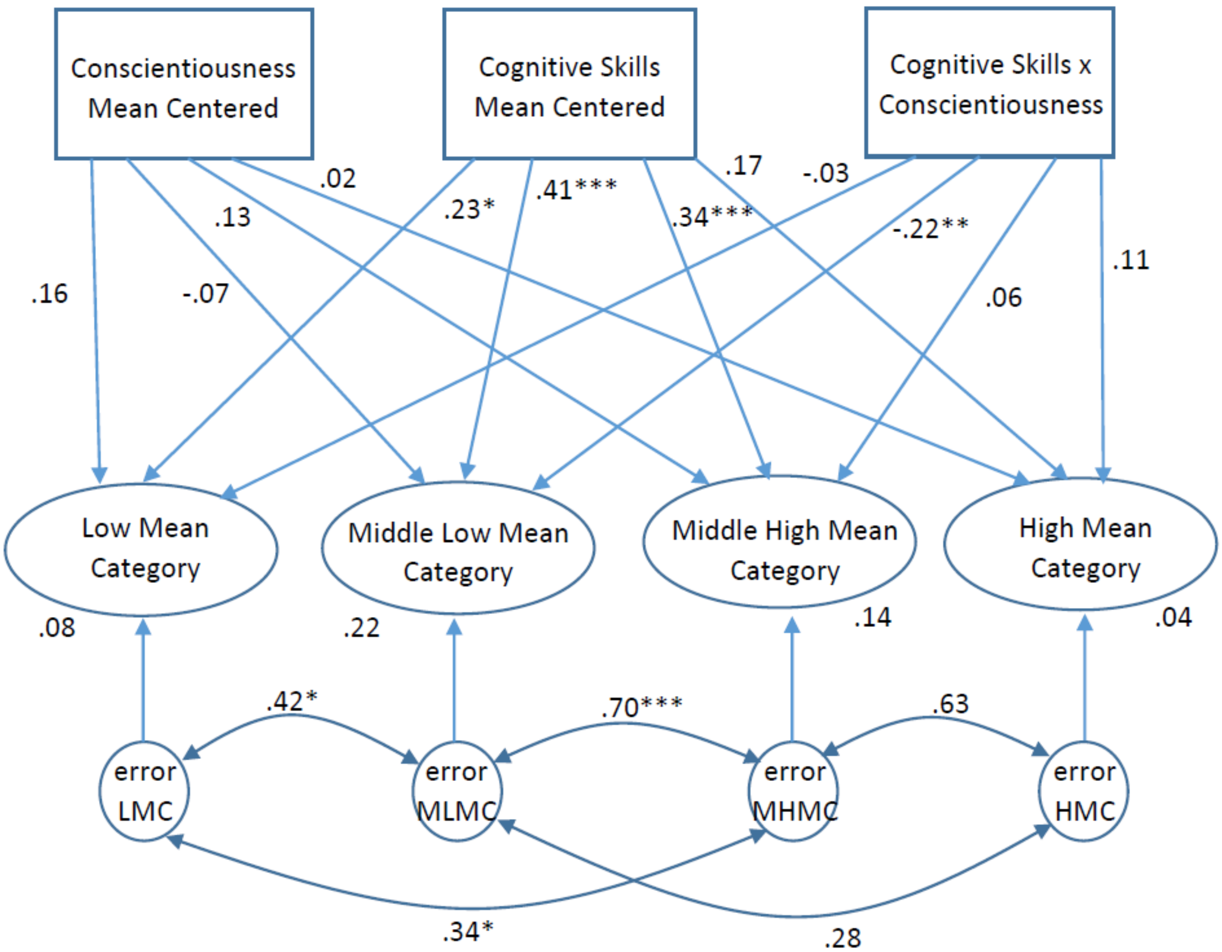


*p < .05, **p < .01, ***p < .001

Figure 29. . Model 13: Path Analysis of Cognitive Skills Interacting with Emotional Stability for Response Time

Note: Path coefficients are standardized. R^2 values for each observed variable for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category.

Model 14 (Figure 30) illustrates the interaction between cognitive skills and conscientiousness on sensitivity. A reasonable model fit was obtained (CFI = 1.000; TLI ρ^2 = 1.009; RMSEA < .001, 90% CI (< .001, < .001); AIC = 153.565; $\chi^2(65)$ = 43.565, p = .981). Individuals with higher performance on the cognitive skills tests were more sensitive to the ambiguous stimuli in the two middle categories, but for the middle low mean condition this relationship was stronger for those low in conscientiousness.

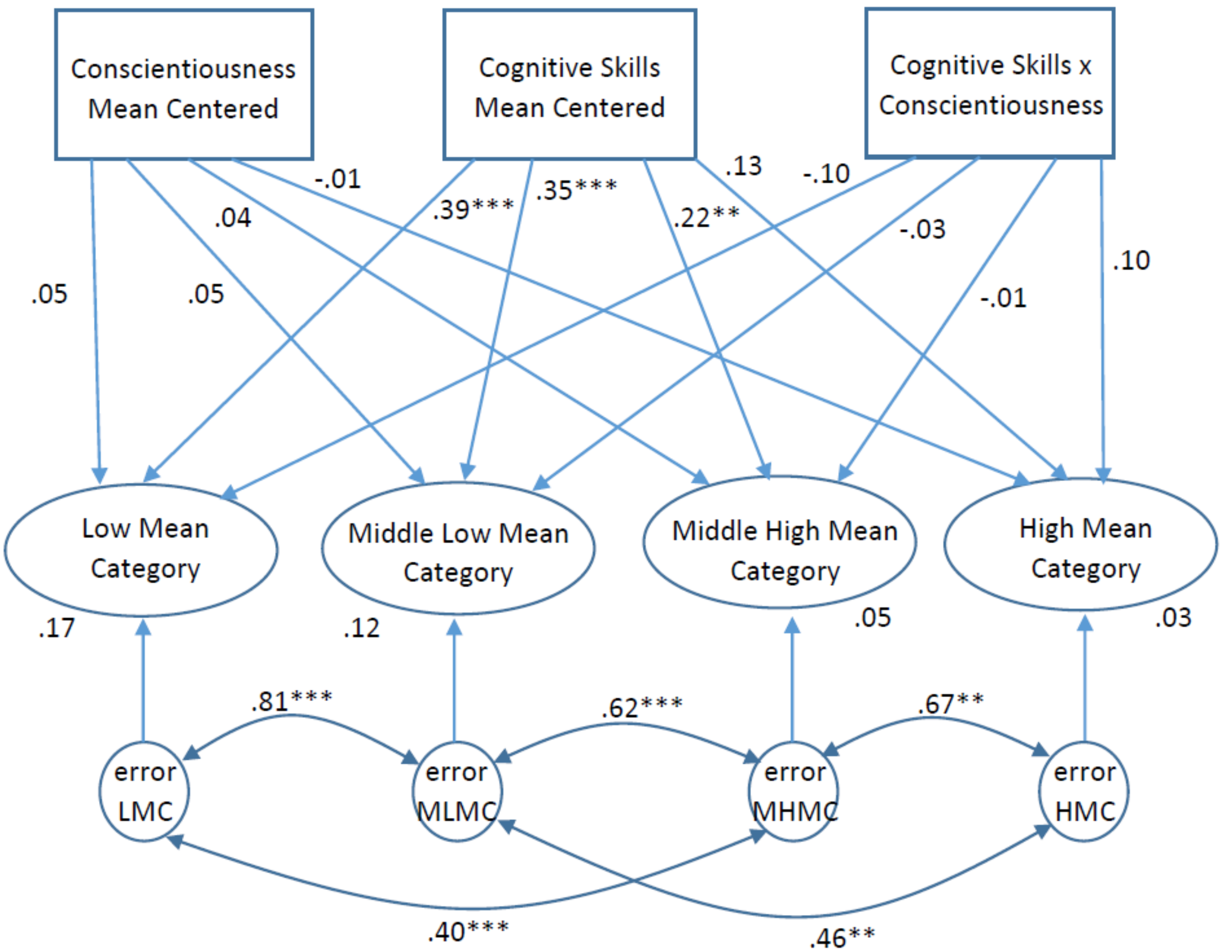


*p < .05, **p < .01, ***p < .001

Figure 30. Model 14: SEM Analysis of Conscientiousness Interacting with Cognitive skills for *d′*

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables for sensitivity factors are not shown.

Model 15 (Figure 31) illustrates the interaction between cognitive skills and conscientiousness on response bias. A reasonable model fit was obtained (CFI = .996; TLI ρ^2 = .992; RMSEA = .018, 90% CI (< .001, .049); AIC = 191.521; $\chi^2(52) = 55.521$, $p = .344$). As the model shows, however, the effect that the cognitive skills factor has on criterion setting does not depend on conscientiousness.



*p < .05, **p < .01, ***p < .001

Figure 31. Model 15: SEM Analysis of Conscientiousness Interacting with Cognitive skills for Index *c*

Note: Path coefficients are standardized. R^2 values for each latent factor for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category. Observed variables for response bias factors are not shown.

Response time was again analyzed with a path analysis (Model 16). A reasonable model fit was obtained (CFI = 1.000; TLI ρ^2 = .997; RMSEA = .033, 90% CI (< .001, .127); AIC = 53.688; $\chi^2(3)$ = 3.688, p = .297). Model 16 is depicted in Figure 32. As the model shows, however, there was no significant interaction effect between conscientiousness and cognitive skills.

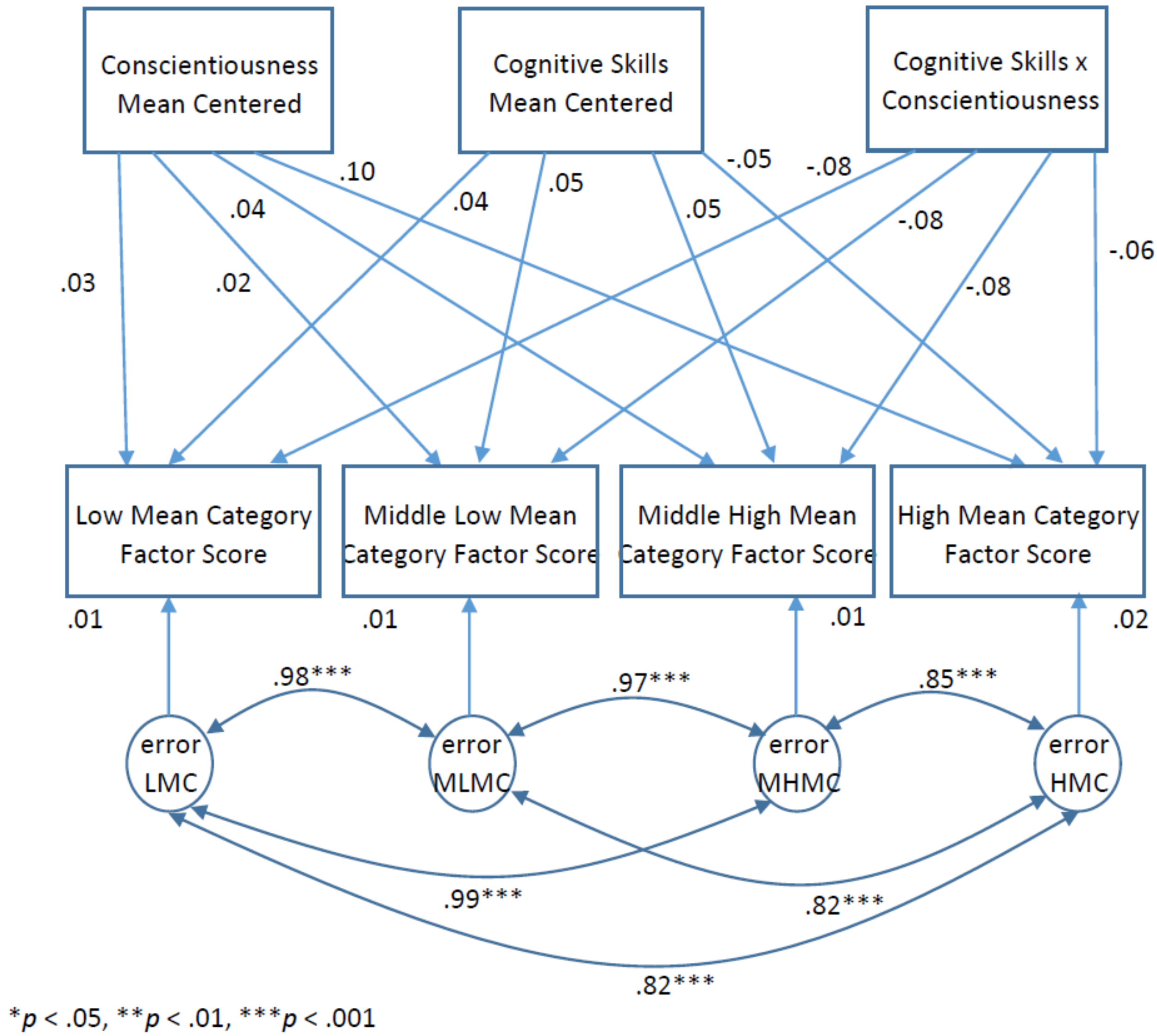


Figure 32. . Model 16: Path Analysis of Cognitive Skills Interacting with Conscientiousness for Response Time

Note: Path coefficients are standardized. R^2 values for each observed variable for performance values are provided next to their respective variable. LMC = Low Mean Category, MLMC = Middle Low Mean Category, MHMC = Middle High Mean Category, and HMC = High Mean Category.

Discussion

Ratings and Response Time. The ANOVAs of participants' responses (Table 11) indicated that both the mean stimulus rating and variability categories for the stimulus influenced participants' responses. Further exploration indicated that within the lower stimulus mean categories (1.0 – 1.49 and 1.5 – 2.49 mean), participants' ratings of the stimulus increased as variability increased. For the higher stimulus mean categories (2.5 – 3.49 and 3.5 – 4.9 mean), participants' ratings were highest in the lowest stimulus variability category and lowest in the medium stimulus variability category. In the lower categories, the higher stimulus variability categories are deviations from absence of threat and so it should make sense that these pictures would result in higher mean ratings from participants.

In the upper categories, the higher stimulus variability categories are deviations from complete presences of threat; it's interesting, however, that there was a consistent pattern among the two higher stimulus mean categories of stimuli of medium variability having lower participant rating scores than stimuli of high variability. A possible explanation for this phenomenon is that, when faced with greater uncertainty in the presence of degree of threat, there is a natural inclination for perceived threat level to increase as the uncertainty grows (i.e., individuals erring on the side of caution). If this were the case, why then would the lowest stimulus variability category be associated with the highest ratings? Because it has the clearest degree of threat. That is, the threat level of images within this category were more consistent than at medium or high variability.

Participants' response times also varied as a function of both stimulus mean category and stimulus variability (see Table 12). Pairwise comparisons revealed that within each stimulus variability category, response time increased significantly as the mean stimulus category increased from low stimulus mean category to middle low stimulus mean category, and then decreased so that the high stimulus mean category was significantly lower than all other stimulus mean categories (however, there was not a significant difference between the response time in the low mean category and the medium high mean category). Thus, participants were fastest responding to high level threats and were slowest when low level threats were presented. This pattern suggests that it takes longer for an individual to respond when presented with a stimulus that is not an immediate threat, and this finding is explored in greater depth in Study 2.

FSDT Measures. Figure 15 illustrates sensitivity effects of stimulus mean category within each variability category. Pairwise comparisons indicated significant differences among all conditions with three exceptions (i.e., between the low stimulus mean category and high stimulus mean category for low and medium variability pictures and between the middle low stimulus mean category and middle high stimulus mean category for high variability pictures). The medium and high variability pictures evince the same pattern, but the low variability was associated with a more dramatic drop in sensitivity for the middle high stimulus mean category. Figure 15 also shows that individuals are more discriminating in the nebulous categories (the middle low and middle high stimulus mean categories) than in the extremes. In part, this may be an artifact of the task: the range of values possible in the middle categories was double that in the extreme categories, yet the same number of pictures were used in each category. In other words, the pictures in the low and high categories had means that varied by at most 0.5 (1 – 1.49 and 3.5 – 4.0, respectively) whereas the pictures in the middle low and middle high categories had means that varied by as much as 1.0 (1.5 – 2.49 and 2.5 – 3.49, respectively). That limitation, may contribute to lower values of d' in the low and high stimulus mean categories.

The higher discrimination in the middle mean categories may also be related to the response time. The longest response time occurred in the middle low stimulus mean category (see Figure 14). It may be the case that the higher discrimination was a result of participants taking longer to respond; that is, the participants may have more carefully considered the more nebulous stimuli. In any event, it is unlikely that higher levels of uncertainty result in individuals being *more* discriminating and further exploration is warranted to determine if this result is an imbalance in width of the domain categories themselves, an artifact of the FSDT procedure itself, a result of mapping functions that fail to completely describe the process, or a by-product of the nature of a threat screening task.

Figure 16 shows that index *c* decreased across all stimulus mean categories; that is, participants became more lenient as threat level increased. Considering only the two lower stimulus mean threat categories, higher variability was associated with lower values of index *c*; for the higher stimulus mean categories index *c* was highest in the medium variability category, but the lowest index *c* score switched from the low variability category to the high variability category between the two mean categories (pairwise comparisons revealed that there was not a significant difference in response bias in the high stimulus mean category between low variability pictures and medium variability pictures; all other mean differences were significant). In the lower stimulus mean categories, the higher variability pictures are deviations from absence of threat, so a propensity to become more lenient in the higher variability categories seems fitting in the context of the task. In the higher stimulus mean categories, the higher variability pictures are deviations from complete presence of threat, so one might argue that the context of the task would lead individuals to become more conservative for stimuli of higher variability. And while that is the case in the transition from low variability to medium variability, the opposite is true in moving from medium variability to high variability. A possible explanation for this phenomenon might again be that individuals are inclined to err on the side of caution (in this case, setting a more lenient criterion) in order to avoid missing a true high-level threat in the presence of increased uncertainty.

Individual Differences. A general SEM model (Model 1) was developed to analyze the effects of visualization and spatial ability on task performance. In this model, all predictors (performance on the five cognitive tests) were allowed to correlate because of the large amount of variance the traits shared, unrelated to the stimulus mean categories. Model 2 analyzed the influence of the five cognitive skills on sensitivity. As seen in Figure 18, higher scores on the cognitive traits were associated with improved sensitivity in the two middle stimulus mean categories but did not contribute significantly to the two extreme stimulus mean categories. That is, in the presence of a clear threat or clear lack of threat, individuals with high and low visualization and spatial skills perform in keeping with one another. However, when a partial threat exists, individuals high in either visualization or spatial ability achieved greater discrimination than those low in all such skills. Thus, it may be the case that the cognitive skills factor assists individuals in evaluating ambiguous stimuli by facilitating recognition of key aspects of a stimulus that indicate presence or absence of threat. It may be beneficial to rotate, realign, or attempt to mentally reassemble an IED in order to recognize high versus low level of threat when the object is presented in a disassembled state. Note that this result is in keeping with previous studies that suggest that object rotation is necessary for recognition (e.g., Tarr and Pinker, 1989) and that recognition is dependent upon object features (e.g., Cheung, Hayward, and Gauthier, 2009).

Model 3 analyzed the influence of the five cognitive skills on response bias. As seen in Figure 19, both visualization and spatial ability result in an individual setting a more conservative criterion in the all but the high stimulus mean category. That is, individuals high on the cognitive skills factor have a higher threshold for what constitutes a threat when only a partial signal is presented. It may be the case that such individuals set a higher criterion because they are engaging in a mental reassembly process instead of deciding threat level purely on the basis of component recognition. This result is similar to the finding of Larsen and Bundesen (1998) who also concluded that mental rotation and translation was used when matching an object to a template. In performing such a mental manipulation, one may become aware of multiple uses for objects present (when not all necessary to construct an IED are present); as a result, one may become more cautious in deciding what constitutes a threat. It is also worth noting that the cognitive factor was not significantly related to response time (Figure 20).

In terms of personality traits, only extraversion and conscientiousness were found to be significantly related to sensitivity, and only for performance in the low stimulus mean category (Figure 21). Extraverts tended to be less discriminating and individuals high in conscientiousness tended to be more discriminating for very low threat levels. While these findings are in keeping with previous research (e.g., Berch and Kanter, 1984; Rose et al., 2002), the restriction of the result to the lowest mean category level may be due to the nature of the task. In a threat detection task, as opposed to many traditional vigilance tasks (e.g., Becker, Warm, Dember, & Howe, 1994; Hitchcock et al., 2003; Szalma et al., 2004), there may be a certain amount of arousal that accompanies higher level threats causing a leveling in performance across different personality traits. The personality traits did not seem to be related to response bias (Figure 22).

Model 7 (Figure 23) analyzed the influence of personality traits on response time, and it is here that personality traits had the largest effect on performance. Across all stimulus mean categories, individuals high on extroversion responded faster than those low on extroversion. Those high on conscientiousness or high on emotional stability took longer to respond in the high and middle high stimulus mean categories. Extroverts may respond faster because the nature of the task (sitting quietly) is contrary to their nature. Humphreys and Revelle (1984) linked performance in extraverts to higher levels of impulsivity; that is, the classification of extraversion may be intertwined with a higher level of impulsivity that gears one to respond faster. Conscientious individuals may spend longer evaluating the higher threat categories to ensure they are correctly analyzing the threat level (i.e., trying to minimize false alarms). Emotionally stable people may be simply be less reactive to perceived threats compared to those lower on this trait, but this finding is also in keeping with work showing that individuals low on neuroticism have a longer response time than those higher on the trait (e.g., Flehmig et al., 2010; Robinson & Tamir, 2005).

The interaction between extraversion and performance on the five cognitive tests was analyzed in Models 8 for sensitivity, Model 9 for response bias, and Model 10 for response time, and yielded no significant influence on performance.

Models 11, 12, and 13 investigated the interaction between emotional stability and performance on the five cognitive tests. Model 11 showed no significant effect of the interaction on sensitivity, but Models 12 and 13 resulted in significant interactions. Figure 28 revealed that, in dealing with more ambiguous stimuli (i.e., in the middle low and middle high stimulus mean categories), individuals low on emotional stability showed a stronger relationship between cognitive skills and criterion setting. Individuals high on emotional stability may experience less arousal when presented with a threat and, thus, may require fewer cognitive resources in assessing that threat. The work of Lommen, Engelhard, and van den Hout (2010) lends credence to this idea, a study in which individuals high in neuroticism were more lenient in declaring an ambiguous signal threatening only when given a longer time delay to avoid the threat. Figure 29 illustrates that higher performance on the cognitive skills attenuated the positive relationship between response time and emotional stability, but only for the highest threat level stimuli. Thus, it may be the case that faster responding to threat stimuli by those low in emotional stability as a result of increased emotional arousal can be dampened by higher levels of relevant cognitive skills. Anxiety is known to impair performance on demanding tasks, and to be particularly hindering in the presence of a threat. That is, lower performance by indviduals high on anxiety is generally attributed to a preoccupation of worries and self-referent thoughts (Matthews, 2008). Thus, individuals low on emotional stability have more cognitive activity interfering with a threat detection task resulting in lower working memory and attentional resources (Matthews et al., 2000). However, among those low on emotional stability, increased performance on the cognitive skills factor (the visualization and spatial ability) contributes more to criterion setting and response time. Thus, individuals high on the cognitive skills factor are able to access alternate cognitive skills to perform the threat detection task.

The interaction between conscientiousness and performance on the five cognitive tests was analyzed in Models 14, 15, and 16. No significant interaction was found for response bias or reaction time, but Model 14 (Figure 30) indicates that individuals low on conscientiousness had a stronger relationship between higher performance on cognitive skills and increased sensitivity, but only in the middle low mean category of stimulus threat. It may be the case that more conscientious individuals tend to more carefully inspect higher threat stimuli than lower threat stimuli, but when threat levels are lower (i.e., low membership ambiguous stimuli), the tendency for conscientious individuals to inspect less carefully may be compensated for by higher cognitive skills. One problem with this interpretation, however, is that conscientious individuals tend to be generally more careful and detail-oriented in performing tasks (Matthews, Deary, & Whiteman, 2009), and would thus likely carefully inspect stimuli regardless of threat level. It may be that those higher in conscientiousness adopt different strategies for effort allocation as a function of likelihood and ambiguity of threat.

CHAPTER 6: STUDY 2

Methods

Participants. A total of 212 undergraduates (131 female, 81 male) at the University of Central Florida participated in the study, ranging in age from 18 to 47 (M = 19.21, SD = 3.579). One female participant's data was omitted because a computer malfunction prevented her from completing the experiment; total analyzed responses were N = 211. Participants were recruited from undergraduate psychology courses through the SONA system, where they earned course credit for their participation. The SONA system was used to screen all participants as having normal or corrected-to-normal vision. All participants completed a brief demographic questionnaire.

Experimental Design. Experiment 2 utilized a 3 (stimulus variability: low, medium, high) x 4 (stimulus mean rating: 1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0) within subjects design. The dependent variables are the threat level (fuzzy membership response category) of the stimulus, length of time the stimulus is viewed prior to response, sensitivity (d'), response bias (index c).

Materials. The same photographs from experiment one were used again in experiment two. Stimuli was presented to the participants on a standard desktop computer. A visual coding system was used to represent the response keys on the keyboard and a visual reminder was located below the computer screen.

Procedure. Participants were requested to complete an informed consent and a brief demographic form. Participants then read the same set of instructions as in experiment one. They also reviewed the same sample stimulus (model ship) and description of the ratings as in experiment one.

Participants then viewed the pre-selected stimuli on a computer monitor without time limit, as the image would advance only when a rating had been entered. Note that this was the major difference in task structure between experiments 1 and 2. In experiment 1, participants did not receive the subsequent trial until they entered a response, but the stimulus to be inspected was presented only for 1600 ms. In experiment 2, the image remained on screen until the participant responded. The time the participant took to respond to each image was recorded along with the rating assigned. After a response was entered, participants were then presented with the next image. The presentation of the stimuli was blocked by variability as in experiment one, and each block was separated by a screen instructing the participants to press the space bar on the keyboard to advance. As in the first experiment, each participant was randomly assigned to one of the six conditions of order of presentation of the blocks of variability. The order of the pictures in each block were predetermined by random assignment.

At the conclusion of the experiment, participants were debriefed.

Results

In analyzing the data, Greenhouse-Geisser was used to correct for violation of sphericity in most F tests involved; where appropriate, the uncorrected degrees of freedom are reported as well as the epsilon used for the correction. The means and standard deviations of participant rating responses and participant median response times are provided in Table 18 and Table 19.

Table 18. ***Descriptive Statistics for Participant Rating Responses (N=211)***

Stimulus Mean	Stimulus Variability	Response Mean	Response Standard Deviation
1.0 – 1.49	Low	1.2322	.39432
	Medium	1.4437	.49778
	High	1.6481	.57514
1.5 – 2.49	Low	2.0841	.65479
	Medium	2.2293	.59482
	High	2.6096	.56305
2.5 – 3.49	Low	3.5089	.43592
	Medium	3.0735	.52915
	High	3.0344	.56088
3.5 – 4.0	Low	3.8205	.33250
	Medium	3.6795	.39921
	High	3.7204	.33852

Table 19. ***Descriptive Statistics for Participant Response Times (N=211)***

Stimulus Mean	Stimulus Variability	Response Mean	Response Standard Deviation
1.0 – 1.49	Low	2037.0735	881.58361
	Medium	2244.4194	1128.89580
	High	2523.6327	1101.73353
1.5 – 2.49	Low	2502.2204	1062.66543
	Medium	2596.9408	1245.21107
	High	2650.8863	1252.98769
2.5 – 3.49	Low	2027.2867	1096.87902
	Medium	2260.9100	1175.61936
	High	2333.7180	1289.01850
3.5 – 4.0	Low	1594.1043	861.10546
	Medium	1884.2678	1034.76981
	High	1796.4005	975.64152

Participant Responses. Participant responses were analyzed with a two-way analysis of variance having four levels of stimulus mean rating (1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0) and three levels of stimulus variability (low, medium, high). All main effects and interactions were statistically significant at the .05 significance level, with η_p^2 values large (see Table 20).

Table 20. ***4 (Stimulus Mean Category) x3 (Stimulus Variability) ANOVA of Participant Responses***

Effect	*df*	*ε*	*SS*	*MS*	*F*	*p*	η_p^2
Stimulus Mean	3	.708	1945.094	648.365	2133.467	<.001	.910
Error	630		191.458	.304			
Stimulus Variability	2		9.262	4.631	39.469	<.001	.158
Error	420		49.280	.117			
Stimulus Mean*Stimulus Variability	6	.784	71.563	11.927	177.894	<.001	.459
Error	1260		84.479	.067			

Additional one-way ANOVAs were computed to further investigate the interactions. Tests of the effects of mean category at each level of signal variability revealed statistically significant main effects for stimulus mean at low stimulus variability, $F(3, 630) = 1979.507$, $p < .001$, $\varepsilon = .826$, $\eta_p^2 = .904$, at medium stimulus variability, $F(3, 633) = 1423.638$, $p < .001$, $\varepsilon = .754$, $\eta_p^2 = .871$, and at high stimulus variability, $F(3, 630) = 1147.826$, $p < .001$, $\varepsilon = .861$, $\eta_p^2 = .845$. At low stimulus variability, there was a significant linear trend, $F(1, 210) = 4320.226$, $p < .001$, $\eta_p^2 = .954$, quadratic trend, $F(1, 210) = 120.179$, $p < .001$, $\eta_p^2 = .364$, and cubic trend, $F(1, 210) = 216.291$, $p < .001$, $\eta_p^2 = .507$. At medium stimulus variability, there was a significant linear trend, $F(1, 211) = 2481.852$, $p < .001$, $\eta_p^2 = .922$, quadratic trend, $F(1, 211) = 18.937$, $p < .001$, $\eta_p^2 = .082$, and cubic trend, $F(1, 211) = 10.416$, $p = .001$, $\eta_p^2 = .047$. At high stimulus variability, there was a significant linear trend, $F(1, 210) = 2287.343$, $p < .001$, $\eta_p^2 = .916$, quadratic trend, $F(1, 210) = 30.646$, $p < .001$, $\eta_p^2 = .127$, and cubic trend, $F(1, 210) = 83.248$, $p < .001$, $\eta_p^2 = .284$. These interactions are depicted in Figure 33. Note that these results replicated the findings of study 1.

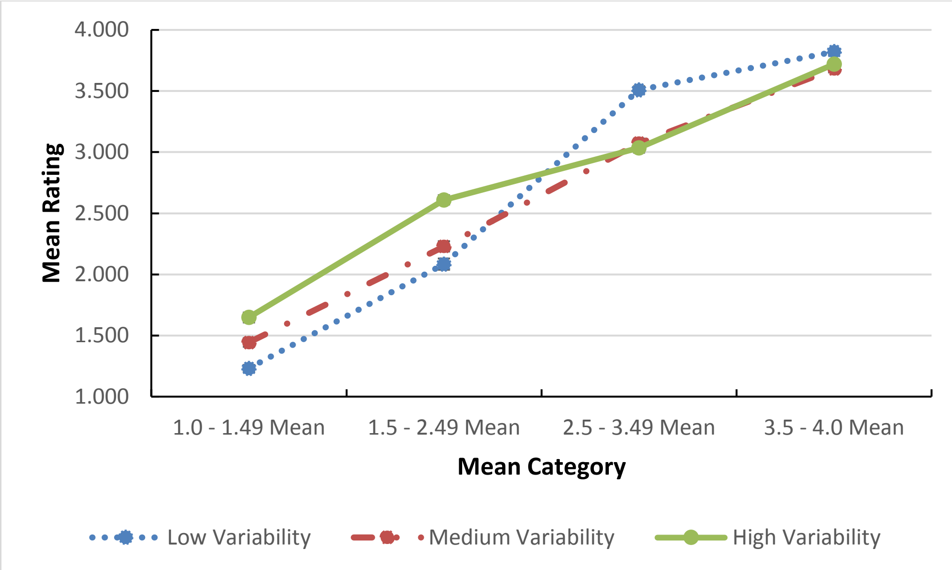


Figure 33. Mean Participant rating as a Function of Stimulus Mean Category in Study 2

Note: Error bars are standard errors.

Median Response Time. Median response times were analyzed with a two-way analysis of variance having four levels of stimulus mean rating (1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0) and three levels of stimulus variability (low, medium, high). All main effects and interactions were statistically significant at the .05 significance level, with a large η_p^2 value for stimulus mean and smaller effects for stimulus variability and the interaction between the factors (see Table 21).

Table 21. ***4x3 ANOVA of Participant Median Response Times***

Effect	*Df*	*ε*	*SS*	*MS*	*F*	*p*	η_p^2
Stimulus Mean	3	.787	219490731.075	73163577.025	97.489	<.001	.317
Error	630		472801732.987	750478.941			
Stimulus Variability	2		36781663.927	18390831.963	8.620	<.001	.039
Error	420		896048649.282	2133449.165			
Stimulus Mean*Stimulus Variability	6	.905	10925164.529	1820860.755	5.453	<.001	.025
Error	1260		420740762.596	333921.240			

Additional one-way ANOVAs were computed to further investigate the interactions. Tests of the effects of mean category at each level of signal variability indicated statistically significant main effects for stimulus mean at low stimulus variability, $F(3, 630) = 63.710$, $p < .001$, $\varepsilon = .894$, $\eta_p^2 = .233$, at medium stimulus variability, $F(3, 633) = 35.887$, $p < .001$, $\varepsilon = .845$, $\eta_p^2 = .14$), and at high stimulus variability, $F(3, 630) = 64.896$, $p < .001$, $\varepsilon = .922$, $\eta_p^2 = .236$. Note that in each case the effects were associated with a large η_p^2. At low stimulus variability, there was a significant linear trend, $F(1, 210) = 65.085$, $p < .001$, $\eta_p^2 = .237$, quadratic trend, $F(1, 210) = 106.628$, $p < .001$, $\eta_p^2 = .337$, and cubic trend, $F(1, 210) = 23.116$, $p < .001$, $\eta_p^2 = .099$. At medium stimulus variability, there was a significant linear trend, $F(1, 210) = 27.798$, $p < .001$, $\eta_p^2 = .116$, quadratic trend, $F(1, 210) = 74.416$, $p < .001$, $\eta_p^2 = .261$, and cubic trend, $F(1, 210) = 12.768$, $p < .001$, $\eta_p^2 = .057$. At high stimulus variability, there was a significant linear trend, $F(1, 210) = 120.378$, $p < .001$, $\eta_p^2 = .364$, and quadratic trend, $F(1, 210) = 50.988$, $p < .001$, $\eta_p^2 = .195$. The interaction is depicted in Figure 34.

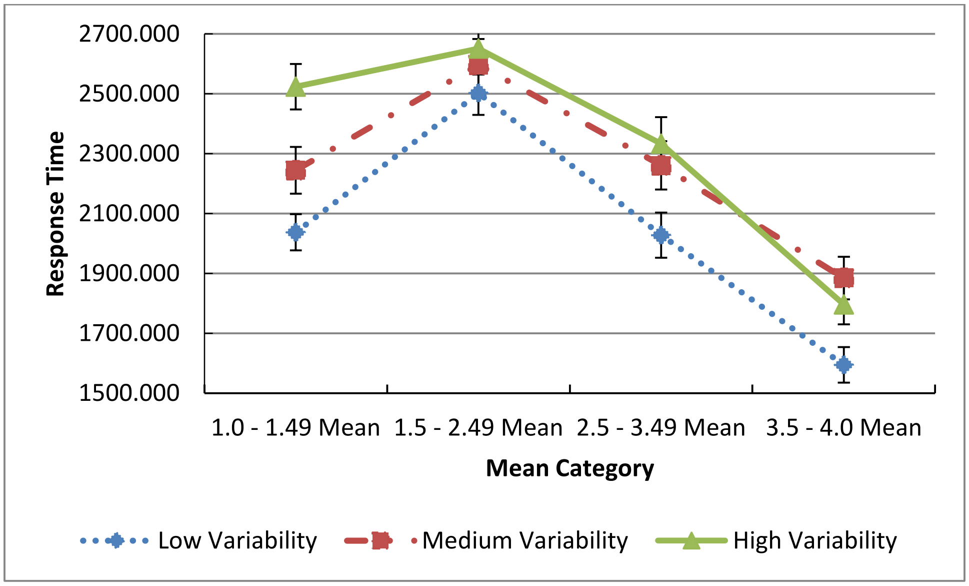


Figure 34. Mean of Median Response Times as a Function of Stimulus Mean Category in Study 2

Note: Error bars are standard errors.

Sensitivity. Sensitivity was analyzed with a two-way analysis of variance having three levels of stimulus variability (low, medium, high) and four levels of stimulus mean rating (1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0). All main effects and interactions were statistically significant at the .05 significance level, with large η_p^2 values for stimulus mean and the interaction effect (see Table 22).

Table 22. ***3 (Stimulus Variability) x 4 (Stimulus Mean Category) ANOVA of Sensitivity***

Effect	*Df*	*ε*	*SS*	*MS*	*F*	*p*	η_p^2
Stimulus Mean	3	.854	89.949	29.983	88.302	<.001	.296
Error	630		213.918	.3402			
Stimulus Variability	2		3.855	1.928	10.998	<.001	.050
Error	420		73.613	.175			
Stimulus Variability *Stimulus Mean	6	.867	45.870	7.645	45.778	<.001	.179
Error	1260		210.425	.167			

Additional one-way ANOVAs were computed to further investigate the interaction. Tests of the effects of mean category at each level of signal variability showed significant main effects for stimulus mean at low stimulus variability, $F(3, 630) = 13.402$, $p < .001$, $\varepsilon = .920$, $\eta_p^2 = .060$, at medium stimulus variability, $F(3, 633) = 105.659$, $p < .001$, $\varepsilon = .831$, $\eta_p^2 = .334$, and at high stimulus variability, $F(3, 630) = 77.410$, $p < .001$, $\varepsilon = .874$, $\eta_p^2 = .269$. At low stimulus variability, there was a significant cubic trend, $F(1, 210) = 32.915$, $p < .001$, $\eta_p^2 = .135$. At medium stimulus variability, there was a significant quadratic trend, $F(1, 211) = 219.565$, $p < .001$, $\eta_p^2 = .510$, and cubic trend, $F(1, 211) = 22.987$, $p < .001$, $\eta_p^2 = .098$. At high stimulus variability, there was a significant linear trend, $F(1, 210) = 20.119$, $p < .001$, $\eta_p^2 = .087$, quadratic trend, $F(1, 210) = 158.491$, $p < .001$, $\eta_p^2 = .430$, and cubic trend, $F(1, 210) = 8.554$, $p = .004$, $\eta_p^2 = .039$. The interaction between the stimulus variability and the stimulus mean rating is illustrated in Figure 35. The results closely match those of study 1

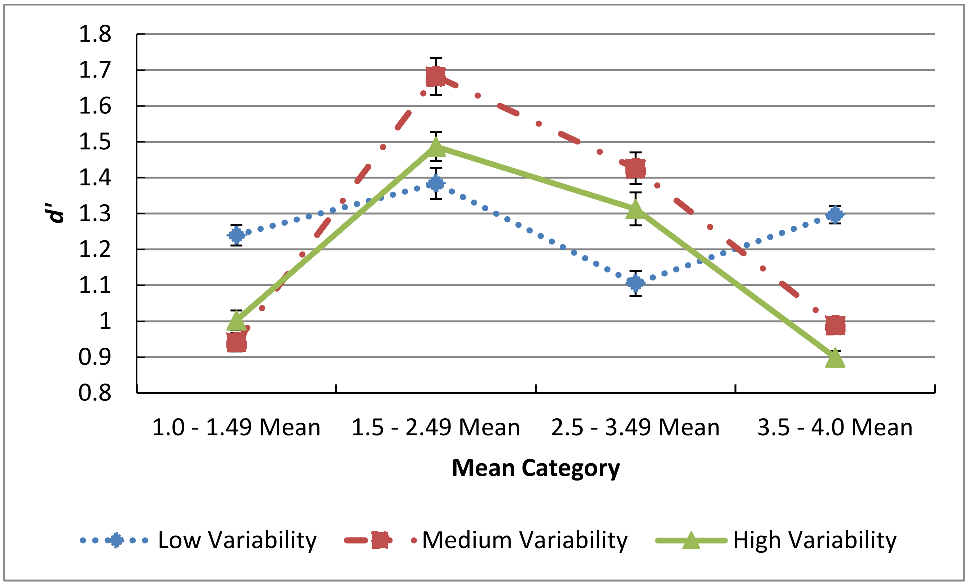


Figure 35. Mean Sensitivity as a Function of Stimulus Mean Category in Study 2

Note: Error bars are standard errors.

Response Bias. Response bias was analyzed with a two-way analysis of variance having three levels of stimulus variability (low, medium, high) and four levels of stimulus mean rating (1.0 – 1.49, 1.5 – 2.49, 2.5 – 3.49, 3.5 – 4.0). All main effects and interactions were statistically significant at the .05 significance level and were associated with values of η_p^2 in the medium-to-large range (see Table 23)

Table 23. ***3 (Stimulus Variability) x 4 (Stimulus Mean Category) ANOVA of Response Bias***

Effect	*df*	*ε*	*SS*	*MS*	*F*	*p*	η_p^2
Stimulus Variability	2		8.867	4.433	24.985	<.001	.106
Error	420		74.527	.177			
Stimulus Mean	3	.854	851.419	283.806	780.293	<.001	.788
Error	630		229.142	.364			
Stimulus Variability *Stimulus Mean	6	.919	33.839	5.640	45.680	<.001	.179
Error	1260		155.564	.123			

Additional one-way ANOVAs were computed to further investigate the interactions. Tests of the effects of mean category at each level of signal variability showed significant main effects for stimulus mean at low stimulus variability, $F(3, 630)=548.526$, $p<.001$, $\varepsilon=.948$, $\eta_p^2=.723$, at medium stimulus variability, $F(3, 633)=451.249$, $p<.001$, $\varepsilon=.909$, $\eta_p^2=.681$, and at high stimulus variability, $F(3, 630)=438.777$, $p<.001$, $\varepsilon=.870$, $\eta_p^2=.676$.

At low stimulus variability, there was a significant linear trend, $F(1, 210) = 1573.142$, $p < .001$, $\eta_p^2 = .882$, quadratic trend, $F(1, 210) = 90.387$, $p < .001$, $\eta_p^2 = .301$, and cubic trend, $F(1, 210) = 65.613$, $p < .001$, $\eta_p^2 = .238$. At medium stimulus variability, there was a significant linear trend, $F(1, 211) = 948.733$, $p < .001$, $\eta_p^2 = .818$, quadratic trend, $F(1, 211) = 30.010$, $p < .001$, $\eta_p^2 = .125$, and cubic trend, $F(1, 211) = 12.462$, $p = .001$, $\eta_p^2 = .056$. At high stimulus variability, there was a significant linear trend, $F(1, 210) = 887.417$, $p < .001$, $\eta_p^2 = .809$, quadratic trend, $F(1, 210) = 16.007$, $p < .001$, $\eta_p^2 = .071$, and cubic trend, $F(1, 210) = 79.059$, $p < .001$, $\eta_p^2 = .274$. Figure 36 illustrates the interaction between stimulus mean category and stimulus variability

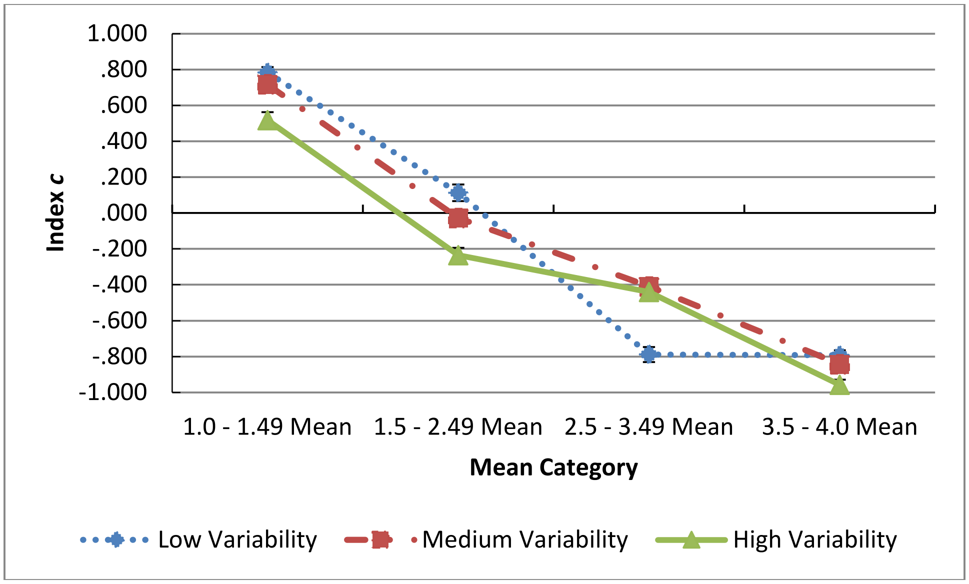


Figure 36. Mean Response Bias as a Function of Stimulus Mean Category in Study 2

Note: Error bars are standard errors.

Structural Equation Modeling. In order to both compare performance patterns with Study 1 and to further explore the relationships among variables by examining their factor structure, the data were evaluated using structural equation modeling. Sensitivity was analyzed in Model 17. This model has a reasonable fit (CFI = .971; TLI ρ^2 = .958; RMSEA = .035, 90% CI (< .000, .061); AIC = 146.043; $\chi^2(46) = 58.043$, p = .110). Figure 37, depicts the structure of Model 17. Stimulus mean category was associated with significant effects in increasing sensitivity in the middle high and middle low stimulus mean categories. Increases in sensitivity were significantly related to stimulus mean category for all of the medium variability category.

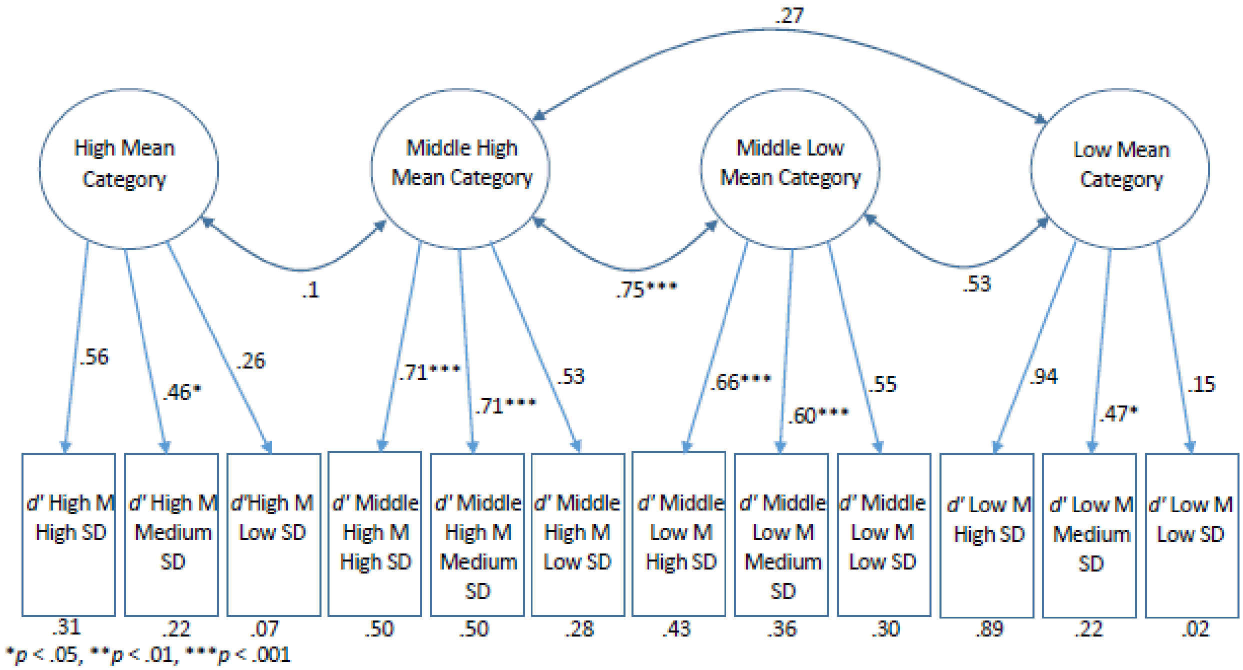


Figure 37. Model 17: SEM Model Analyzing *d'* Under Unconstrained Time

Note: Path coefficients are standardized. R^2 values for each observed variable for performance values are provided next to their respective variable. M = Mean, SD = Standard Deviation

Model 18 analyzes response bias using the same latent structure as Model 17. This model also has a reasonable fit (CFI = .982; TLI ρ^2 = .969; RMSEA = .052, 90% CI (.023, .076); AIC = 163.225; $\chi^2(38)$ = 59.225, p = .015). Figure 38, depicts the structure of Model 18. The interaction between stimulus mean category and stimulus variability was significantly related to response bias in every category.

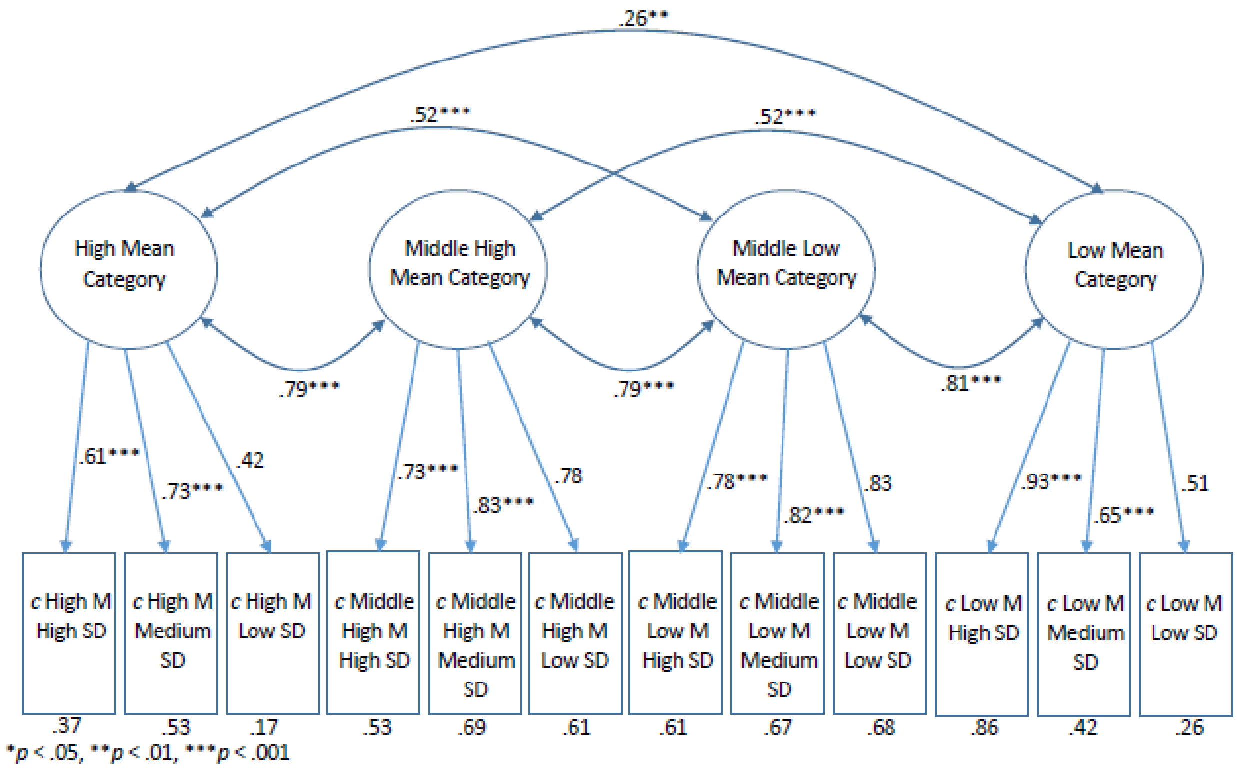


Figure 38. Model 18: SEM Model Analyzing Index *c* Under Unconstrained Time

Note: Path coefficients are standardized. R^2 values for each observed variable for performance values are provided next to their respective variable. M = Mean, SD = Standard Deviation

The latent structure of the previous two models failed to converge to reasonable solution in analyzing response time. Although the fit indices appeared reasonable (CFI = .995; TLI ρ^2 = .987; RMSEA = .038, 90% CI (< .000, .072); AIC = 163.373; $\chi^2(24)$ = 31.373, p = .143), illegal values of estimates were obtained (i.e., negative variances, correlations greater than 1; Kline, 2011). Restructuring by variability and collapsing across stimulus mean category yielded a model (Model 19) with a reasonable fit (CFI = .949; TLI ρ^2 = .923; RMSEA = .094, 90% CI (.075, .114); AIC = 218.151; $\chi^2(44)$ = 126.151, p < .001). Figure 39, depicts the structure of Model 19. The interaction between stimulus mean category and stimulus variability was significantly related to response time in every category.

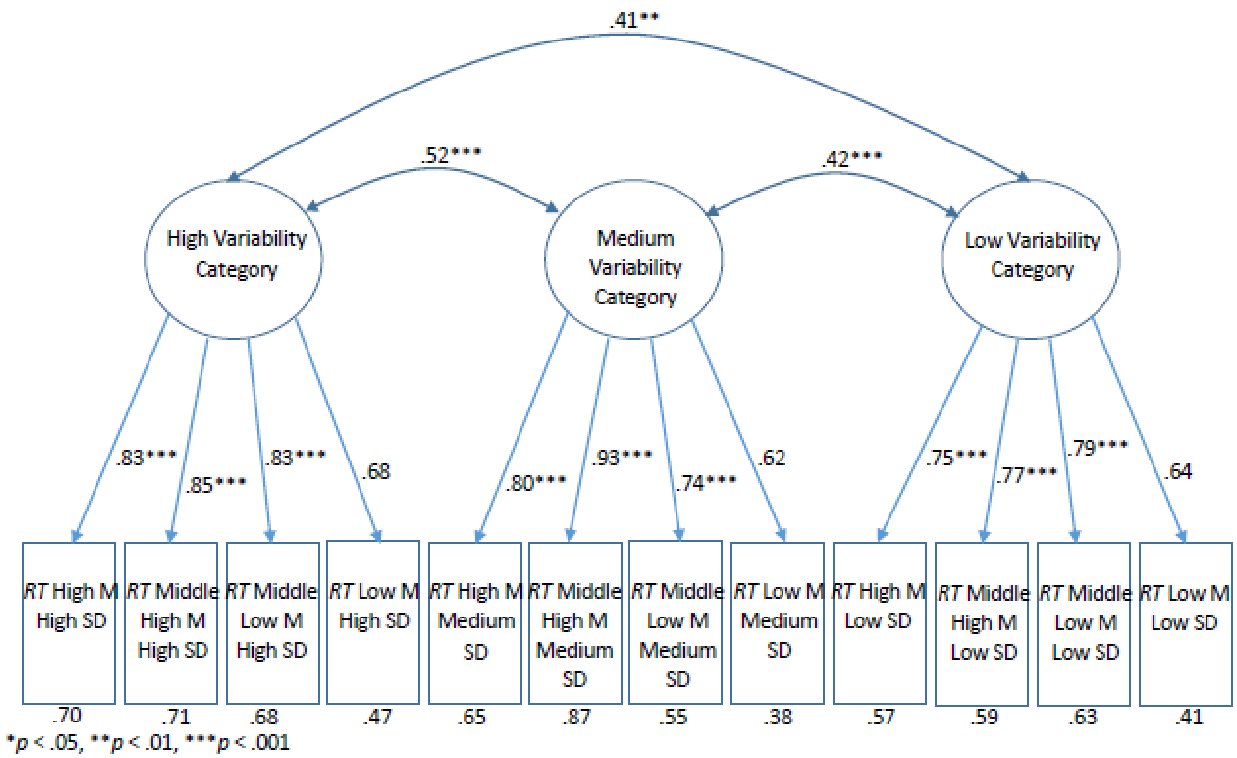


Figure 39. Model 19: SEM Model Analyzing Response Time Under Unconstrained Time

Note: Path coefficients are standardized. R^2 values for each observed variable for performance values are provided next to their respective variable. M = Mean, SD = Standard Deviation

Discussion

A comparison of Figure 13 with Figure 33 shows that the pattern of participant responses was similar across Study 1 and Study 2. The similarities are also seen in the analyses of sensitivity (Figure 15 with Figure 35) and response bias (Figure 16 with Figure 36). Thus, performance outcomes were similar across the two studies, and the mean ratings corresponded to those of the participants in the preliminary study.

Model 17 (Figure 37) analyzes the effect of stimulus mean category on *d'* with the time constraint of Study 1 removed. Similar to Study 1, higher levels of sensitivity were obtained for the middle stimulus mean categories, and this is reflected in the higher regression weights of the model. Thus, the results of this experiment again confirm the unexpected result of Study 1 that discrimination is greater in the ambiguous categories (middle low and middle high stimulus mean categories) than in the crisp categories (low and high stimulus mean categories).

The analysis of response bias, Model 18 (Figure 38), shows that criterion setting is predicted by the stimulus mean category across all levels of stimulus variability, as all regression weights in the model were significant. Model 19 (Figure 39) indicates that response time is predicted by stimulus variability across all levels of stimulus mean category, as all regression weights in the model were also significant.

It had been hypothesized that response times would follow an inverted-U shape, with the shortest response times occurring on the extremes (low stimulus mean category and high stimulus mean category) and the longest response times in the middle. However, Figure 34 shows that is not quite the case. The high stimulus mean category did produce the shortest response times, but the low stimulus mean category had a higher than anticipated response time. In fact, pairwise comparisons indicated significant differences between each stimulus mean category except the low and middle high. Although it was predicted that participants would take a roughly equal amount of time in the low stimulus mean category and high stimulus mean category, participants take longer to declare a complete absence of threat than to declare a complete presence of threat. However, this result is in keeping with the assertion of Hancock, Masalonis, and Parasuraman (2000), based on the research of Treisman and Gelade (1980), that decision time is longer for a non-signal than for a signal, and is exacerbated by the presence of noise. In fact, the results of this research show that decision time is longest when a partial signal is present, but the magnitude of that signal is low (the middle low stimulus mean category). Thus, the results obtained here provide additional evidence for that assertion.

CHAPTER 7: GENERAL DISCUSSION

The present work establishes differences in performance based on individual characteristics (spatial ability, visualization ability, extraversion, emotional stability, and conscientiousness). Just as importantly, however, this work also establishes differences in performance based on characteristics of the signal presented (i.e., signal membership and variability within that signal membership category), which has not been previously established in other signal detection tasks. The use of FSDT allows the modeling of the ambiguity of the signal to be reflected in the signal membership category rather than the noise present, as is the case in traditional SDT. In doing so, performance across studies varied as a function of both stimulus mean category and stimulus variability. Future work in FSDT should take into account that the nature of the stimulus itself (signal membership and variability) will be a factor in performance measures.

Study 1 provides a connection between individual difference measures and performance on a fuzzy signal detection task. Individuals high in the cognitive traits factor (spatial ability and visualization) show increased sensitivity in the presence of ambiguous stimuli on a threat detection task. Further, increased performance on the cognitive skills factor contributes to a more conservative criterion setting in all conditions but the most obvious presence of threat. One direct application of this result is that threat screening situations can be optimized by selecting individuals high in spatial ability or visualization. Additionally, performance can be improved by integrating technology into the process (e.g., implementing automated decision aids), particularly for low-level threats where individuals demonstrated the longest inspection time and performance varied greatly as a function of individual difference measures. Further, monitoring levels of arousal that might influence impulsivity may be warranted in a threat screening task.

What is not addressed by this research is whether there are other characteristics that predict as well, or better, than these two cognitive traits. Because both spatial ability and visualization can be learned, it may be the case that higher study skills, which aids learning, or general intelligence may predict the same outcomes.

In this particular threat detection task, personality characteristics did not influence performance to the extent anticipated. However, because extraversion had a negative impact and conscientiousness had a positive impact on sensitivity for low threat levels, it would be appropriate to screen for these characteristics when assigning personnel to a threat detection task. Perhaps because of higher levels of impulsivity, extraverts are likely to answer quickly, and thus not discriminate well, when at very low levels of signal. On the other hand, conscientious individuals are more likely to spend extra effort at the lower signal levels to identify anything that could potentially be a threat. Together with the cognitive traits of visualization and spatial ability, all three personality traits (extraversion, conscientiousness, and emotional stability) had an effect on at least one measure of performance.

Study 2 demonstrated that, for a threat detection task involving ambiguous signals, individuals take more time to decide on a non-signal than they do on a signal, particularly when noise is present. Further, the confirmation of results of Study 1 that Study 2 provided illuminates an interesting fact: for a threat detection task involving ambiguous stimuli, unbounding stimulus presentation time does not affect performance on FSDT measures. Prior to experimentation, it was expected that unbounding time would have increased sensitivity, but that did not prove to be the result. It appears as though sensitivity and criterion setting are independent of time above a minimum level required for stimulus processing, indicating that the task may be in the data-limited range of information processing (Norman & Bobrow, 1975). Note that in experiment 1, it was the stimulus presentation time that was limited. The response window for each trial was unbounded in both studies. Thus, differences in response time between the two experiments reflect time available for stimulus observation rather than time to respond, per se.

Additional research along these lines may answer several questions. First, is the independence of time and both sensitivity and criterion setting unique to this context? That is, what about the context of identifying decomposed IEDs in a natural setting lead to that result? The overall low levels of *d'* in Study 2 indicate that the task itself was challenging by nature. An unanswered question is whether increased time does not improve performance on all difficult signal detection tasks.

Additional mathematical questions surrounding this research remain open. One question that developed from these experiments is whether the range of the values spanning the domain of the mapping functions needs to be consistent across categories in order to model a detection task adequately. Note that a continuous mapping of participants' responses would circumvent this problem; however, the question itself is theoretically interesting and has practical applications in situations, such as this research, where assigning stimuli into bins is necessary. Is it the case that changing the bin width (of the stimulus domain) will affect analysis of the FSDT measures. In general, additional work on mapping functions is needed.

In terms of response time, this research showed that the decision of non-signal takes longer than the decision of full signal. An interesting question would be to investigate decision time related to transition of signals, similar to the transitioning signals used in Fortenbaugh et al. (2015). That is, instead of transitioning from absence of signal to presence of signal, if participants were asked to categorize an item transitioning from one signal to another (e.g., a star transitioning into a planet in a video game, where both valuable signals in terms of scoring points because each involves a different task), would response time now take on the inverted quadratic shape because both extremes are full presence of signal, or would the response time mimic the results found in Study 2, almost as though the participants were cognitively assigning one signal to the "non-signal" status and the other as "full signal" status?

Future research may answer the question of whether abilities underlying spatial abilities (such as general intelligence) have as strong of an effect on performance. Similarly, a comparison of the effects of training with and without the identified cognitive traits on performance would prove a useful measure to ensure performance of a screening task is optimized. Additionally, investigation into alternate cognitive characteristics that might improve performance on difficult detection tasks is warranted.

Some situations, such as threat detection, do not lend themselves to crisp categorizations of signal and non-signal. FSDT provides a robust tool for decision analysis in the presence of such uncertainty. The research conducted here links individual difference measures with performance on a fuzzy task and provides an application for FSDT analysis.

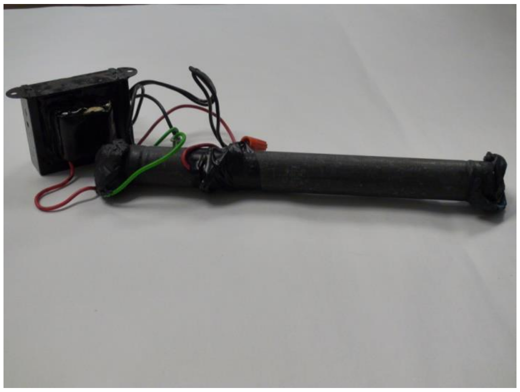
APPENDIX A: EXPERIMENTAL INSTRUCTIONS

A1. Study 1 Instructions

For this experiment, you will be asked to evaluate images of improvised explosive devices (IEDs) or their parts and judge the degree of threat of the object based on how "bomb-like" they look. Here is the situation:

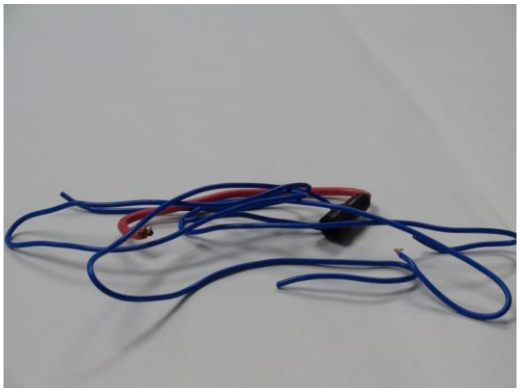
Imagine that you are a new member of a military squad whose primary mission is to secure areas by identifying and removing all potential threats (e.g., guns, bombs, or parts thereof) so that the area may be repopulated by civilians. Your squad has been called in to clear a local office building where terrorists used portions of the building as a cover for their operation. The terrorists have been arrested by military police, and members of your squad will secure the building so that the civilians employed there may re-enter. Your job is to view images projected by an unmanned ground vehicle that has been sent into the building and prioritize each situation into a category based on the perceived level of threat, or how "bomb-like" the components appear. The ratings will be given to the members of your squad designated to enter the building, and they will use these ratings to visit the most critical situations first (the highest category, then proceeding down as time allows).

The terrorists were constructing IEDs using some parts that might commonly be found in most homes or office buildings.



Here you see examples of the terrorists' assembled bombs. The parts that make the bombs are shown on the next several screens. As you can see, the bombs are made from common parts but need a device that can trigger the bomb remotely, like a cell phone, and need a power source, such as a battery or an electronic device.

Wires: Notice that, when viewed from a distance, these wires look very similar to wires commonly used to connect computer equipment (such as connecting a printer to a tower).



Wires: Notice that, when viewed from a distance, these wires look very similar to wires commonly used to connect phone lines to the main network in an office building.

Plastic explosive: The only purpose of this object is to be used as an explosive device

C-4: This is another form of plastic explosive. The only purpose of this material is to be detonated as a bomb.

Power source: This device is used to ignite the bomb. Notice that this is constructed from common computer parts.

Remote triggering device: A cell phone is used to remotely trigger the bomb. It is common knowledge that a cell phone is a familiar device for an ordinary person to possess and people often leave their cell phones lying about their office.

Calculator: The calculator is used as a power source to ignite the bomb. Be aware that it is not uncommon to find a calculator in an office environment.

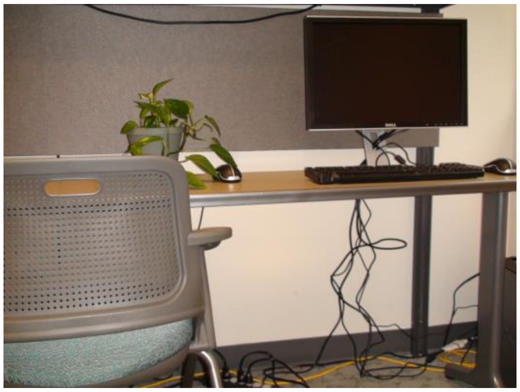
Lead pipe: This is used as casing for a bomb (e.g., "pipe bomb"). In general, there would be no other purpose for this to be in an office building.

Soda can: This is used as casing for a bomb. However, it is also common for people to drink soda at work, so you may find this left in an office environment.

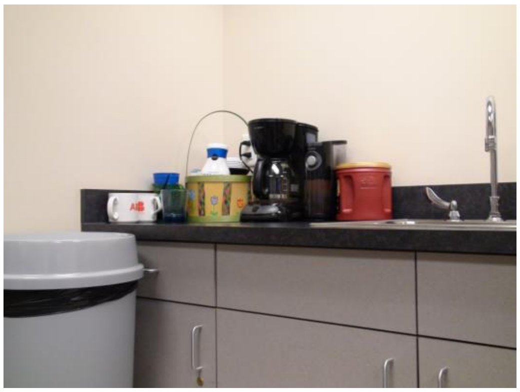
Objects can often be divided into several components. When some of these components are missing, the purpose of the object may change and it may no longer be recognizable as that object. For example, when we go to watch a movie, we expect to see certain critical pieces: a plot, props, a leading actor, and a supporting actor. Lacking some of these components, such as missing a supporting actor, may not make the movie seem less movie-like. In fact, there could be an entire movie comprised only of a plot, props, and a single leading actor and we might herald this film as a spectacular indie-style film. However, lacking both a leading actor and a supporting actor makes the film considerably less movie-like. Such a film could exist, perhaps as a documentary showing only still-life photos, but it would not be what we traditionally think of as a movie. If we remove a different component, the plot, then a leading actor, a supporting actor and props alone do not make much of a movie at all. These three objects alone would barely be reminiscent of a movie at all because they are lacking a very critical component.

Some objects that are not IEDs (and therefore do not pose an immediate threat) still pose a degree of threat because they have features similar to IEDs. Your job is to remotely view areas in the building and determine the threat level based on the contents of the room. The rooms you will be viewing (without any IED parts present) are shown on the next several screens.

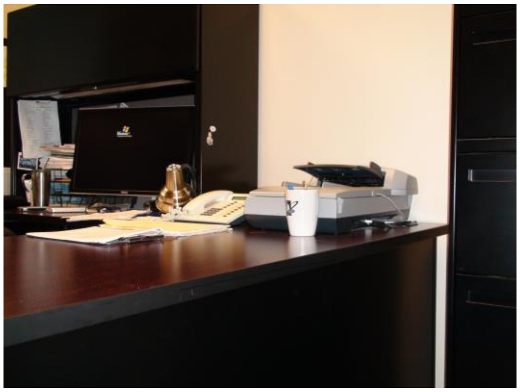
General Office Space



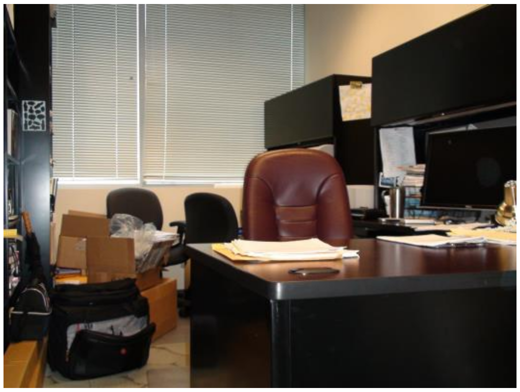
A Break Room



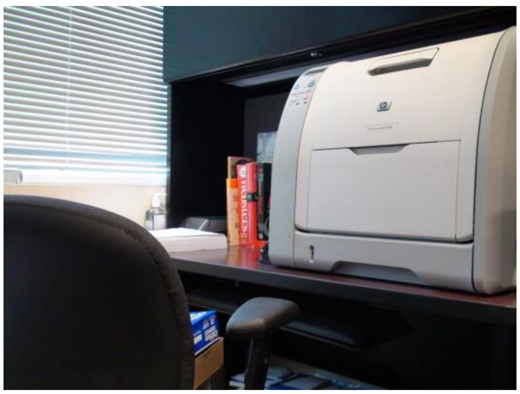
An Individual's Office



An Individual's Office



An Individual's Office



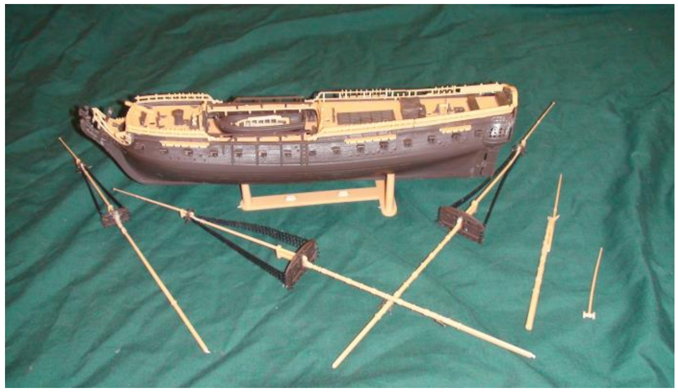
An Individual's Office

For each image you inspect, you will rate the threat level. You would rate a threat as high if you think that the room should be searched and cleared immediately (i.e., you are confident that the room contains bomb parts left by the terrorists) and you should rate a threat as low if you feel that the room can be searched last or not at all (i.e., you are confident that the room contains no bomb parts left by the terrorists). The ratings you will use are:

1	2	3	4
Green: You are certain that no IED threat is present. The room is clear so the members of your squad do not need to visit the room.	**Yellow low priority:** A suspicious item or set of items is present, but do not appear to be an imminent threat at this time. However, the room should be checked if time permits.	**Yellow high priority:** A highly suspicious item or set of items is present; the room should be flagged for further inspection. After all rooms in the red category have been cleared, the squad members will search the rooms marked in this category and confiscate all suspicious items.	**Red:** You are certain that an immediate bomb threat is present. Rooms marked in this category will be the first to be searched by members of your squad, and the bomb or bomb materials will be rendered harmless.

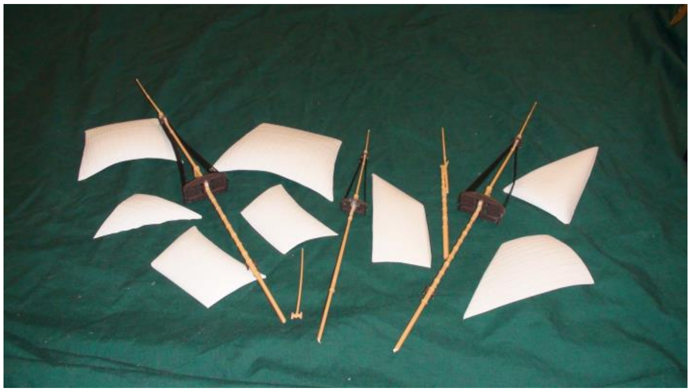
The idea that objects are made of separate pieces that hold different levels of purpose for that object can be difficult to understand. For example, if we were attempting to detect the presence of the pirate ship depicted above, and code that presence using the four categories described on the previous screen, we might provide the ratings shown on the following four screens.

Red: In this picture, we see all of the necessary parts to label this a pirate ship (such as the assembled hull, mast, and sails), even though it is not a fully assembled pirate ship.

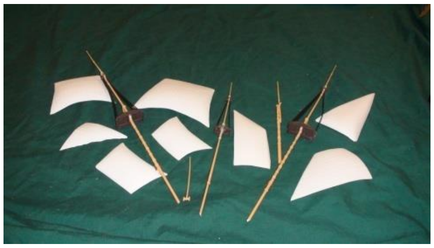


Yellow high priority: In this picture, we see most of the necessary parts to label this a pirate ship. Here, we are missing the sails, preventing the ship from being able to take to sea. However, all other components are present.

Yellow low priority: In this picture, we see that the object resembles a pirate ship. Here, we have an assembled hull, which alone is not enough for the ship to take sail. Further, this may not be the hull of a pirate ship, because the hull by itself does not signify that; it could be the hull of a battle ship or it could be used as a tugboat to bring in other ships.



Green: In this picture, we see the unassembled masts and sails of the pirate ship. Alone, there is no indication that these parts are very related to a pirate ship at all.



1

2

3

4

Remember that in this experiment, you are trying to decide how "bomb-like" an object is. Because many of the items are used in a common office environment, you should carefully scan the environment to determine if the presence of these items is a threat. For example, if you had been told that a television remote control could be used as a detonator but was commonly used in the office environment for the security cameras, then seeing a remote control by itself should not necessarily alarm you unless it is out of place relative to its surroundings (e.g., found outside of the security room) or paired with enough other materials that can be used to construct a bomb. Be aware that you may also see other innocuous personal items (e.g., cameras, umbrellas, medical supplies, food items, etc.) that individuals may bring into an office environment for various (nonthreatening) reasons.

Rating the degree of threat of an object can be difficult. Please ask your experimenter for clarification if any instructions are unclear. When you feel confident that you understand the task, please press the space bar to view the first image. After viewing the picture, press the key corresponding to the appropriate threat level (red, yellow high priority, yellow low priority, or green) when prompted. Please wait for the prompt to enter your response.

A2. Study 2 Alternate Conclusion

Rating the degree of threat of an object can be difficult. Please ask your experimenter for clarification if any instructions are unclear. When you feel confident that you understand the task, please press the space bar to view the first image. For each picture, you should rate its threat level by pressing the key corresponding to the appropriate threat level (red, yellow high priority, yellow low priority, or green).

APPENDIX B: DEMOGRAPHICS QUESTIONNAIRE

Participant Number:________________

Date:_______________

Demographic Questionnaire

1. What is your gender? (circle one) Male Female

2. What is your age?__________

3. How many hours do you work on a computer per day? (circle one)

   0 < 1 hour 1-2 hours 3-4 hours 5-6 hours 7+ hours

4. How many hours a day to you play video games on average? (circle one)

   0 < 1 hour 1-2 hours 3-4 hours 5-6 hours 7+ hours

   IF YOU DO PLAY VIDEO GAMES, please describe what type:

   ____

   ____

5. Are you or have you ever been involved in a threat detection task? (circle one)

   Yes No

   IF YES, please describe:____

   ____

6. Do you have normal or corrected to normal vision?

   Yes No

   IF NO, please describe:____

   ____

APPENDIX C: IRB DOCUMENTS

C1. Informed Consent

Detecting Threats from Constituent Parts: A Fuzzy Signal Detection Theory Analysis of Individual Differences

Informed Consent

Principal Investigator(s):	Sidra Van De Car
Faculty Supervisor:	James L. Szalma, Ph.D.
Investigational Site(s):	University of Central Florida, Department of Psychology

Introduction: Researchers at the University of Central Florida (UCF) study many topics. To do this we need the help of people who agree to take part in a research study. You are being invited to take part in a research study which will include about 400 people at UCF. You have been asked to take part in this research study because you are a current UCF student. You must be 18 years of age or older and have 20/20 vision (or corrected to 20/20 vision) to be included in the research study.

The person doing this research is Sidra Van De Car of UCF, Department of Psychology. Because the researcher is a graduate student, she is being guided by James L. Szalma, a UCF faculty supervisor in Psychology.

What you should know about a research study:

- Someone will explain this research study to you.
- A research study is something you volunteer for.
- Whether or not you take part is up to you.
- You should take part in this study only because you want to.
- You can choose not to take part in the research study.
- You can agree to take part now and later change your mind.
- Whatever you decide it will not be held against you.

- Feel free to ask all the questions you want before you decide.

Purpose of the research study: The purpose of this study is to examine characteristics that may affect performance of a rating task. Aspects of an environment perceived, as well as personality and cognitive characteristics of the perceiver, may influence judgements. This research seeks to describe some of the aspects that may influence performance.

What you will be asked to do in the study: Participation will consist of filling out brief questionnaires and inventories then participating in a computer-based task where you will be asked to assign different categories to pictures. You do not have to answer every question or complete every task. You will not lose any benefits if you skip questions or tasks.

Location: UCF Department of Psychology, PeRL lab.

Time required: We expect that you will be in this research study for 1.5 hours.

Risks: There are no reasonably foreseeable risks or discomforts involved in taking part in this study. However, if at any time you feel uncomfortable, inform the researcher and the study will be terminated without penalty or loss of benefit.

Benefits: There are no expected benefits to you for taking part in this study.

Alternatives: Instead of being in this research study, your choices may include: participating in other research studies announced through the SONA system or talking to your individual instructor about alternatives for course credit.

Compensation or payment: For your participation, you will receive 1.5 SONA credits.

Confidentiality: We will limit your personal data collected in this study to people who have a need to review this information. Our interest as researchers is in how people in general respond to the pictures, not how any one individual responds to the pictures. For this reason, all data collected will be reported in aggregate form only and at no time will individual participant information be matched to data in any meaningful way through which identity might be divined. Although every effort will be made to maintain the confidentiality of your participation, should data be compromised you will be notified if you provide us contact information. Further, you may refuse to answer any questions which make you uncomfortable. We cannot promise complete secrecy. Organizations that may inspect and copy your information include the IRB and other representatives of UCF.

Study contact for questions about the study or to report a problem: If you have questions, concerns, or complaints, or think the research has hurt you, talk to: Sidra Van De Car, Graduate

Student, Applied Experimental and Human Factors Psychology Program, College of Sciences, (407) 582-2032, sidra@knights.ucf.edu, or Dr. James L. Szalma, Faculty Supervisor, Department of Psychology at (407) 823-0920 or by email at james.szalma@ucf.edu.

IRB contact about your rights in the study or to report a complaint: Research at the University of Central Florida involving human participants is carried out under the oversight of the Institutional Review Board (UCF IRB). This research has been reviewed and approved by the IRB. For information about the rights of people who take part in research, please contact: Institutional Review Board, University of Central Florida, Office of Research & Commercialization, 12201 Research Parkway, Suite 501, Orlando, FL 32826-3246 or by telephone at (407) 823-2901. You may also talk to them for any of the following:

- Your questions, concerns, or complaints are not being answered by the research team.
- You cannot reach the research team.
- You want to talk to someone besides the research team.

C2. Debriefing

Post Participation Information

Thank you for your participation in this study. The purpose of this study was to examine characteristics that may influence performance of a rating task. In this research, your ratings of different threat levels for various pictures of components of Improvised Explosive Devices (IEDs) were recorded. Your responses, when combined with the responses of other participants, will allow us to determine an appropriate number of responses for participants, personality and cognitive characteristics that influence ratings, or properties of the stimulus that influence decision time. This research will help in our understanding of what individuals use to assess situational threat.

If you have further questions about your participation in this study, please contact

Sidra Van De Car
Phone: (407) 582-2032
E-mail: sidra@knights.ucf.edu

or the faculty advisior

James Szalma
Phone: (407) 823-0920
E-mail: James.Szalma@ucf.edu

C3. IRB Approval of Human Research

University of Central Florida

University of Central Florida Institutional Review Board
Office of Research & Commercialization
12201 Research Parkway, Suite 501
Orlando, Florida 32826-3246
Telephone: 407-823-2901 or 407-882-2276
www.research.ucf.edu/compliance/irb.html

Approval of Human Research

From: **UCF Institutional Review Board #1**
FWA00000351, IRB00001138

To: **Sidra Van De Car**

Date: **July 14, 2015**

Dear Researcher:

On 07/14/2015, the IRB approved the following minor modifications to human participant research until 10/08/2015 inclusive:

Type of Review:	IRB Addendum and Modification Request Form
Modification Type:	An additional Informed Consent has been approved for use. This consent document has two changes to the original: the duration of participation time has been decreased to 0.5 hours and "Part 2" has been added to the title to differentiate the two parts of the study on the SONA system. Both parts of the study were approved initially and the original Informed Consent will continue to be used with new study participants.
Project Title:	Detecting Threats from Constituent Parts: A Fuzzy Signal Detection Theory Analysis of Individual Differences
Investigator:	Sidra Van De Car
IRB Number:	SBE-14-10526
Funding Agency:	
Grant Title:	
Research ID:	N/A

The scientific merit of the research was considered during the IRB review. The Continuing Review Application must be submitted 30days prior to the expiration date for studies that were previously expedited, and 60 days prior to the expiration date for research that was previously reviewed at a convened meeting. Do not make changes to the study (i.e., protocol, methodology, consent form, personnel, site, etc.) before obtaining IRB approval. A Modification Form **cannot** be used to extend the approval period of a study. All forms may be completed and submitted online at https://iris.research.ucf.edu .

If continuing review approval is not granted before the expiration date of 10/08/2015, approval of this research expires on that date. When you have completed your research, please submit a Study Closure request in iRIS so that IRB records will be accurate.

Use of the approved, stamped consent document(s) is required. The new form supersedes all previous versions, which are now invalid for further use. Only approved investigators (or other approved key study personnel) may solicit consent for research participation. Participants or their representatives must receive a copy of the consent form(s).

All data, including signed consent forms if applicable, must be retained and secured per protocol for a minimum of five years (six if HIPAA applies) past the completion of this research. Any links to the identification of participants should be maintained and secured per protocol. Additional requirements may be imposed by your funding agency, your department, or other entities. Access to data is limited to authorized individuals listed as key study personnel.

In the conduct of this research, you are responsible to follow the requirements of the Investigator Manual.

On behalf of Sophia Dziegielewski, Ph.D., L.C.S.W., UCF IRB Chair, this letter is signed by:

Joanne Muratori

Signature applied by Joanne Muratori on 07/14/2015 01:35:15 PM EDT

IRB manager

APPENDIX D: TABLES

SEM Model 1: Latent Factor Structure

Table 24. Regression Weights for SEM Model 1

Path	Estimate	Standardized Estimate	Standard Error	*p*
Cognitive Skills → S1	1.000	.532		
Cognitive Skills → S2	.407	.739	.050	< .001
Cognitive Skills → VZ1	.692	.812	.091	< .001
Cognitive Skills → VZ2	.280	.781	.038	< .001
Cognitive Skills → VZ3	1.125	.885	.143	<.001

Table 25. Variances SEM Model 1

	Estimate	Standard Error	*p*
Cognitive Skills	361.618	93.284	< .001
Error S1	917.141	95.714	< .001
Error S2	49.899	5.810	< .001
Error VZ1	89.481	11.750	< .001
Error VZ2	18.166	2.232	< .001
Error VZ3	126.203	22.787	<.001

Table 26. Squared Multiple Correlations SEM Model 1

Factor	S1	S2	VZ1	VZ2	VZ3
Estimate	.283	.546	.659	.610	.784

SEM Model 2: Analysis of Sensitivity in Experiment 1

Table 27. Regression Weights for SEM Model 2

Path	Estimate	Standardized Estimate	Standard Error	*p*
Cognitive Skills → High Mean Category	.001	.192	.001	.386
Cognitive Skills → Middle High Mean Category	.004	.377	.001	.002
Cognitive Skills → Middle Low Mean Category	.010	.445	.002	< .001
Cognitive Skills → Low Mean Category	.002	.231	.001	.066
High Mean Category → *d'* High Mean Low SD	1.000	.179		
High Mean Category → *d'* High Mean Medium SD	1.837	.392	1.901	.334
High Mean Category → *d'* High Mean High SD	1.080	.268	1.070	.313
Middle High Mean Category → *d'* Middle High Mean Low SD	1.000	.390		
Middle High Mean Category → *d'* Middle High Mean Medium SD	2.728	.730	.652	< .001
Middle High Mean Category → *d'* Middle High Mean High SD	2.108	.637	.494	< .001
Middle Low Mean Category → *d'* Middle Low Mean High SD	.477	.362	.118	< .001
Middle Low Mean Category → *d'* Middle Low Mean Medium SD	.971	.620	.188	< .001
Middle Low Mean Category → *d'* Middle Low Mean Low SD	1.000	.696		
Low Mean Category → *d'* Low Mean Low SD	1.000	.349		
Low Mean Category → *d'* Low Mean Medium SD	1.842	.722	.792	.020
Low Mean Category → *d'* Low Mean High SD	1.219	.416	.419	.004
Cognitive Skills → S1	1.000	.535		
Cognitive Skills → S2	.403	.735	.049	< .001
Cognitive Skills → VZ1	.684	.808	.089	< .001
Cognitive Skills → VZ2	.279	.782	.037	< .001
Cognitive Skills → VZ3	1.119	.886	.141	<.001

Table 28. Covariances SEM Model 2

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle Low Mean ↔ Error Low Mean	.018	.359	.009	.041
Error High Mean ↔ Error Middle Low Mean	.006	.241	.007	.379
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.083	.336	.021	< .001
Error Middle Low Mean High SD ↔ Error Low Mean High SD	.041	.214	.015	.005
Error Low Mean High SD ↔ Error High Mean Medium SD	-.017	-.145	.009	.060
Error Low Mean High SD ↔ Error High Mean Low SD	-.015	-.104	.010	.144
Error Middle Low Mean Medium SD ↔ Error High Mean Low SD	-.041	-.204	.016	.011
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-.042	-.218	.016	.009
Error Middle High Mean Low SD ↔ Error Middle Low Mean Low SD	.033	.171	.017	.048
Error High Mean High SD ↔ Error Middle High Mean Low SD	.026	.206	.009	.006
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Low SD	-.040	-.191	.022	.072
Error Middle High Mean High SD ↔ Error Low Mean High SD	.030	.165	.015	.045
Error Low Mean High SD ↔ Error Low Mean Low SD	-.020	-.144	.013	.120
Error S1 ↔ Error S2	45.568	.212	17.275	.008

Table 29. Variances SEM Model 2

	Estimate	Standard Error	*p*
Cognitive Skills	366.298	93.582	< .001
Error High Mean	.005	.008	.531
Error Middle High Mean	.031	.013	.015
Error Middle Low Mean	.138	.036	< .001
Error Low Mean	.019	.011	.097
Error High Mean High SD	.077	.010	< .001
Error Middle High Mean High SD	.236	.039	< .001
Error Middle Low Mean High SD	.260	.028	< .001
Error Low Mean High SD	.141	.018	< .001
Error High Mean Medium SD	.094	.019	< .001
Error Middle High Mean Medium SD	.236	.057	< .001
Error Middle Low Mean Medium SD	.261	.039	< .001
Error Low Mean Medium SD	.062	.025	.014
Error High Mean Low SD	.154	.017	< .001
Error Middle High Mean Low SD	.202	.022	< .001
Error Middle Low Mean Low SD	.184	.035	< .001
Error Low Mean Low SD	.144	.017	< .001
Error S1	912.461	95.130	< .001
Error S2	50.417	5.818	< .001
Error VZ1	91.228	11.728	< .001
Error VZ2	18.104	2.210	< .001
Error VZ3	125.442	22.161	<.001

Table 30. Squared Multiple Correlations SEM Model 2

Factor	Estimate
Low Mean Category	.054
Middle Low Mean Category	.198
Middle High Mean Category	.142
High Mean Category	.037
VZ3	.785
VZ2	.611
VZ1	.653
S2	.541
S1	.286
d’ Low Mean Low SD	.121
d’ Middle Low Mean Low SD	.484
d’ Middle High Mean Low SD	.152
d’ High Mean Low SD	.032
d’ Low Mean Medium SD	.521
d’ Middle Low Mean Medium SD	.385
d’ Middle High Mean Medium SD	.534
d’ High Mean Medium SD	.154
d’ Low Mean High SD	.173
d’ Middle Low Mean High SD	.131
d’ Middle High Mean High SD	.406
d’ High Mean High SD	.072

SEM Model 3: Analysis of Response Bias in Experiment 1

Table 31. Regression Weights for SEM Model 3

Path	Estimate	Standardized Estimate	Standard Error	*p*
Cognitive Skills → High Mean Category	.001	.151	< .001	.154
Cognitive Skills → Middle High Mean Category	.003	.229	.001	.010
Cognitive Skills → Middle Low Mean Category	.009	.367	.002	< .001
Cognitive Skills → Low Mean Category	.004	.412	.001	< .001
High Mean Category → *c* High Mean Low SD	1.000	.271		
High Mean Category → *c* High Mean Medium SD	3.788	.696	1.265	.003
High Mean Category → *c* High Mean High SD	1.935	.409	.662	.003
Middle High Mean Category → *c* Middle High Mean Low SD	1.000	.530		
Middle High Mean Category → *c* Middle High Mean Medium SD	1.744	.883	.302	< .001
Middle High Mean Category → *c* Middle High Mean High SD	1.150	.593	.165	< .001
Middle Low Mean Category → *c* Middle Low Mean High SD	.765	.629	.089	< .001
Middle Low Mean Category → *c* Middle Low Mean Medium SD	1.084	.827	.110	< .001
Middle Low Mean Category → *c* Middle Low Mean Low SD	1.000	.774		
Low Mean Category → *c* Low Mean Low SD	1.000	.501		
Low Mean Category → *c* Low Mean Medium SD	1.806	.695	.298	< .001
Low Mean Category → *c* Low Mean High SD	2.654	.796	.427	< .001
Cognitive Skills → S1	1.000	.537		
Cognitive Skills → S2	.405	.742	.050	< .001
Cognitive Skills → VZ1	.689	.816	.090	< .001
Cognitive Skills → VZ2	.279	.785	.037	< .001
Cognitive Skills → VZ3	1.104	.877	.140	<.001

Table 32. Covariances SEM Model 3

Path	Covariance Estimate	Correlation Estimate	Standard Error	p
Error High Mean ↔ Error Middle High Mean	.016	.679	.006	.004
Error High Mean ↔ Error Middle Low Mean	.017	.466	.006	.007
Error Middle High Mean ↔ Error Middle Low Mean	.077	.621	.017	< .001
Error Middle High Mean ↔ Error Low Mean	.021	.410	.006	< .001
Error Middle Low Mean ↔ Error Low Mean	.064	.807	.013	< .001
Error Middle Low Mean Low SD ↔ Error Low Mean Low SD	.018	.135	.012	.127
Error Middle Low Mean Medium SD ↔ Error Low Mean Medium SD	.009	.070	.016	.560
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Medium SD	.024	.250	.016	.142
Error High Mean Medium SD ↔ Error Middle High Mean Low SD	.012	.081	.014	.379
Error High Mean Medium SD ↔ Error Middle Low Mean Low SD	-.066	-.517	.015	< .001
Error High Mean Medium SD ↔ Error Middle High Mean Medium SD	.006	.065	.022	.794
Error Low Mean High SD ↔ Error Middle Low Mean Low SD	.048	.309	.018	.007
Error Low Mean High SD ↔ Error Middle High Mean Medium SD	.031	.283	.017	.070
Error Middle Low Mean High SD ↔ Error Middle High Mean Low SD	.070	.335	.018	< .001
Error Middle Low Mean High SD ↔ Error Low Mean High SD	.049	.274	.016	.002
Error Middle High Mean High SD ↔ Error Low Mean High SD	.060	.330	.017	< .001
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.097	.477	.019	< .001
Error High Mean High SD ↔ Error Middle High Mean Low SD	.058	.341	.014	< .001
Error High Mean High SD ↔ Error Middle Low Mean Medium SD	-.033	-.257	.013	.016
Error High Mean High SD ↔ Error Middle Low Mean High SD	.029	.177	.014	.045
Error High Mean High SD ↔ Error Middle High Mean High SD	.067	.404	.015	< .001

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle Low Mean High SD ↔ Error High Mean Medium SD	-.003	-.018	.015	.859
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-.022	-.187	.012	.059
Error Middle Low Mean High SD ↔ Error Middle High Mean Medium SD	.060	.496	.018	< .001
Error Middle High Mean High SD ↔ Error Middle High Mean Low SD	.050	.236	.020	.011
Error High Mean High SD ↔ Error Low Mean Low SD	-.019	-.153	.009	.029
Error High Mean High SD ↔ Error Middle Low Mean Low SD	-.041	-.294	.014	.004
Error High Mean High SD ↔ Error Low Mean High SD	.016	.111	.013	.231
Error Low Mean High SD ↔ Error High Mean Medium SD	.023	.175	.016	.141
Error S1 ↔ Error S2	43.930	.207	17.191	.011

Table 33. Variances SEM Model 3

	Estimate	Standard Error	*p*
Cognitive Skills	368.167	93.977	< .001
Error High Mean	.007	.004	.076
Error Middle High Mean	.080	.023	< .001
Error Middle Low Mean	.193	.033	< .001
Error Low Mean	.033	.010	< .001
Error High Mean High SD	.132	.015	< .001
Error Middle High Mean High SD	.206	.026	< .001
Error Middle Low Mean High SD	.199	.023	< .001
Error Low Mean High SD	.162	.030	< .001
Error High Mean Medium SD	.108	.031	< .001
Error Middle High Mean Medium SD	.073	.034	.032
Error Middle Low Mean Medium SD	.121	.025	< .001
Error Low Mean Medium SD	.139	.020	< .001
Error High Mean Low SD	.089	.009	< .001
Error Middle High Mean Low SD	.217	.025	< .001
Error Middle Low Mean Low SD	.149	.023	< .001
Error Low Mean Low SD	.119	.013	< .001
Error S1	910.593	95.170	< .001
Error S2	49.399	5.763	< .001
Error VZ1	87.897	11.589	< .001
Error VZ2	17.868	2.205	< .001
Error VZ3	135.224	22.745	<.001

Table 34. Squared Multiple Correlations SEM Model 3

Factor	Estimate
Low Mean Category	.169
Middle Low Mean Category	.135
Middle High Mean Category	.052
High Mean Category	.023
VZ3	.768
VZ2	.616
VZ1	.666
S2	.550
S1	.288
c Low Mean Low SD	.251
c Middle Low Mean Low SD	.599
c Middle High Mean Low SD	.281
c High Mean Low SD	.074
c Low Mean Medium SD	.483
c Middle Low Mean Medium SD	.683
c Middle High Mean Medium SD	.779
c High Mean Medium SD	.485
c Low Mean High SD	.634
c Middle Low Mean High SD	.396
c Middle High Mean High SD	.352
c High Mean High SD	.167

SEM Model 4: Analysis of Response Time in Experiment 1

Table 35. Regression Weights for SEM Model 4

Path	Estimate	Standardized Estimate	Standard Error	*p*
Cognitive Skills → Low Mean Category	-1.711	-.197	1.062	.107
Cognitive Skills → Middle Low Mean Category	.274	.037	1.076	.799
Cognitive Skills → Middle High Mean Category	1.278	.272	1.033	.216
Cognitive Skills → High Mean Category	-.865	-.192	.609	.156
High Mean Category → Median *RT* High Mean Low SD	1.000	.321		
High Mean Category → Median *RT* High Mean Medium SD	1.190	.356	.473	.012
High Mean Category → Median *RT* High Mean High SD	1.439	.459	.680	.034
Middle High Mean Category → Median *RT* Middle High Mean High SD	1.756	.334	1.469	.232
Middle High Mean Category → Median *RT* Middle High Mean Medium SD	.441	.101	.534	.409
Middle High Mean Category → Median *RT* Middle High Mean Low SD	1.000	.265		
Middle Low Mean Category → Median *RT* Middle Low Mean High SD	.211	.057	.240	.380
Middle Low Mean Category → Median *RT* Middle Low Mean Medium SD	2.913	.633	9.060	.748
Middle Low Mean Category → Median *RT* Middle Low Mean Low SD	1.000	.246		
Low Mean Category → Median *RT* Low Mean High SD	.299	.099	.413	.469
Low Mean Category → Median *RT* Low Mean Medium SD	.574	.206	.713	.421
Low Mean Category → Median *RT* Low Mean Low SD	1.000	.506		
Cognitive Skills → S1	1.000	.529		
Cognitive Skills → S2	.408	.738	.051	< .001
Cognitive Skills → VZ1	.696	.812	.092	< .001
Cognitive Skills → VZ2	.283	.786	.038	< .001
Cognitive Skills → VZ3	1.126	.882	.144	<.001

Table 36. Covariances SEM Model 4

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle Low Mean Low SD ↔ Error Low Mean Low SD	92768.367	.601	14153.768	< .001
Error Middle High Mean Low SD ↔ Error Low Mean Low SD	56486.178	.624	8320.569	< .001
Error Middle High Mean Low SD ↔ Error Middle Low Mean Low SD	94537.975	.532	14401.405	< .001
Error High Mean Low SD ↔ Error Low Mean Low SD	47125.757	.666	6636.345	< .001
Error High Mean Low SD ↔ Error Middle Low Mean Low SD	65707.532	.474	11274.167	< .001
Error High Mean Low SD ↔ Error Middle High Mean Low SD	53357.225	.655	7078.387	< .001
Error Low Mean Medium SD ↔ Error Middle Low Mean Low SD	8349.125	.034	13391.338	.533
Error Low Mean Medium SD ↔ Error High Mean Low SD	3804.189	.034	6466.286	.556
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	151.813	.001	10807.792	.989
Error Middle Low Mean Medium SD ↔ Error High Mean Low SD	-7409.021	-.059	9038.325	.412
Error Middle High Mean Medium SD ↔ Error Low Mean Low SD	-3354.782	-.031	5836.086	.565
Error Middle High Mean Medium SD ↔ Error High Mean Low SD	-5426.136	-.056	5415.892	.316
Error Middle High Mean Medium SD ↔ Error Low Mean Medium SD	85193.630	.492	13678.345	< .001
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Medium SD	145690.833	.763	19767.308	< .001
Error High Mean Medium SD ↔ Error Middle High Mean Low SD	7205.453	.083	4292.993	.093
Error High Mean Medium SD ↔ Error Low Mean Medium SD	60902.694	.507	9832.917	< .001
Error High Mean Medium SD ↔ Error Middle Low Mean Medium SD	88453.943	.666	13635.662	< .001
Error High Mean Medium SD ↔ Error Middle High Mean Medium SD	64351.159	.626	8748.292	< .001
Error Low Mean High SD ↔ Error High Mean Medium SD	-14128.667	-.107	6565.593	.031
Error Middle Low Mean High SD ↔ Error Low Mean Low SD	-16323.571	-.114	7308.240	.026
Error Middle Low Mean High SD ↔ Error Low Mean High SD	127985.781	.506	19704.252	< .001
Error Middle High Mean High SD ↔	-9318.983	-.039	12670.160	.462

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle Low Mean Low SD				
Error Middle High Mean High SD ↔ Error Low Mean Medium SD	10660.537	.054	9945.351	.284
Error Middle High Mean High SD ↔ Error Middle Low Mean Medium SD	-1252.516	-.006	14180.316	.930
Error Middle High Mean High SD ↔ Error High Mean Medium SD	-1147.664	-.010	6423.704	.858
Error Middle High Mean High SD ↔ Error Low Mean High SD	128828.818	.594	18184.732	< .001
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	142070.269	.630	19140.921	< .001
Error High Mean High SD ↔ Error Middle Low Mean Low SD	-18008.942	-.138	7522.249	.017
Error High Mean High SD ↔ Error Middle High Mean Medium SD	6823.979	.075	4946.298	.168
Error High Mean High SD ↔ Error Low Mean High SD	53883.925	.460	9647.406	< .001
Error High Mean High SD ↔ Error Middle Low Mean High SD	57010.912	.468	9977.768	< .001
Error High Mean High SD ↔ Error Middle High Mean High SD	63058.269	.603	9471.133	< .001
Error S1 ↔ Error S2	46.731	.218	17.370	.007
Error Middle Low Mean Medium SD ↔ Error Low Mean Medium SD	194879.825	.872	24519.745	< .001

Table 37. Variances SEM Model 4

	Estimate	Standard Error	*p*
Cognitive Skills	358.294	92.905	< .001
Error High Mean	7040.753	4208.380	.094
Error Middle High Mean	7306.425	6989.864	.296
Error Middle Low Mean	19401.044	60873.508	.750
Error Low Mean	26062.549	34299.277	.447
Error High Mean High SD	56528.794	9253.562	< .001
Error Middle High Mean High SD	193544.950	29398.257	< .001
Error Middle Low Mean High SD	262855.529	25922.469	< .001
Error Low Mean High SD	243151.401	24252.331	< .001
Error High Mean Medium SD	71444.804	8813.683	< .001
Error Middle High Mean Medium SD	147890.995	14883.422	< .001
Error Middle Low Mean Medium SD	246784.887	513569.890	.631
Error Low Mean Medium SD	202353.446	23242.866	< .001
Error High Mean Low SD	63589.918	7360.809	< .001
Error Middle High Mean Low SD	104262.144	12602.975	< .001
Error Middle Low Mean Low SD	302611.692	67220.236	< .001
Error Low Mean Low SD	78682.833	35189.990	.025
Error S1	920.465	95.968	< .001
Error S2	50.044	5.814	< .001
Error VZ1	89.442	11.713	< .001
Error VZ2	17.750	2.199	< .001
Error VZ3	129.448	22.709	< .001

Table 38. Squared Multiple Correlations SEM Model 4

Factor	Estimate
Low Mean Category	.039
Middle Low Mean Category	.001
Middle High Mean Category	.074
High Mean Category	.037
VZ3	.778
VZ2	.619
VZ1	.660
S2	.544
S1	.280
Median *RT* Low Mean Low SD	.256
Median *RT* Middle Low Mean Low SD	.060
Median *RT* Middle High Mean Low SD	.070
Median *RT* High Mean Low SD	.103
Median *RT* Low Mean Medium SD	.042
Median *RT* Middle Low Mean Medium SD	.400
Median *RT* Middle High Mean Medium SD	.010
Median *RT* High Mean Medium SD	.126
Median *RT* Low Mean High SD	.010
Median *RT* Middle Low Mean High SD	.003
Median *RT* Middle High Mean High SD	.112
Median *RT* High Mean High SD	.211

SEM Model 5: Analysis of Sensitivity Across Personality Traits in Experiment 1

Table 39. Regression Weights for SEM Model 5

Path	Estimate	Standardized Estimate	Standard Error	*p*
Conscientiousness Scale Sum → Low Mean Category	.005	.207	.003	.037
Conscientiousness Scale Sum → Middle Low Mean Category	-.006	-.105	.005	.223
Conscientiousness Scale Sum → Middle High Mean Category	.004	.116	.003	.168
Conscientiousness Scale Sum → High Mean Category	.001	.126	.001	.549
Emotional Stability Scale Sum → Low Mean Category	-.002	-.088	.002	.331
Emotional Stability Scale Sum → Middle Low Mean Category	.006	.132	.004	.128
Emotional Stability Scale Sum → Middle High Mean Category	< .001	.009	.002	.912
Emotional Stability Scale Sum → High Mean Category	-.001	-.284	.001	.449
Extraversion Scale Sum → Low Mean Category	-.005	-.242	.002	.019
Extraversion Scale Sum → Middle Low Mean Category	-.005	-.111	.004	.200
Extraversion Scale Sum → Middle High Mean Category	-.002	-.102	.002	.224
Extraversion Scale Sum → High Mean Category	-.001	-.328	.001	.440
High Mean Category → *d'* High Mean Low SD	1.000	.074		
High Mean Category → *d'* High Mean Medium SD	3.528	.314	4.465	.430
High Mean Category → *d'* High Mean High SD	3.694	.381	4.629	.425
Middle High Mean Category → *d'* Middle High Mean High SD	1.956	.626	.409	< .001
Middle High Mean Category → *d'* Middle High Mean Medium SD	2.677	.779	.562	< .001
Middle High Mean Category → *d'* Middle High Mean Low SD	1.000	.415		
Middle Low Mean Category → *d'* Middle Low Mean High SD	.627	.428	.137	< .001
Middle Low Mean Category → *d'* Middle Low Mean Medium SD	1.123	.654	.209	< .001

Path	Estimate	Standardized Estimate	Standard Error	p
Middle Low Mean Category → *d'* Middle Low Mean Low SD	1.000	.636		
Low Mean Category → *d'* Low Mean High SD	1.302	.512	.400	.001
Low Mean Category → *d'* Low Mean Medium SD	1.371	.620	.419	.001
Low Mean Category → *d'* Low Mean Low SD	1.000	.402		

Table 40. Covariances SEM Model 5

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle Low Mean ↔ Error Low Mean	.027	.010	.472	.005
Error High Mean ↔ Error Middle Low Mean	.004	.005	.373	.449
Error Middle High Mean ↔ Error Middle Low Mean	.052	.015	.695	< .001
Error Middle High Mean ↔ Error Low Mean	.012	.005	.388	.013
Error High Mean ↔ Error Middle High Mean	.004	.005	.715	.429
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.079	.021	.316	< .001
Error Middle Low Mean High SD ↔ Error Low Mean High SD	.034	.014	.193	.016
Error Low Mean High SD ↔ Error High Mean Medium SD	-.018	.009	-.160	.039
Error Low Mean High SD ↔ Error High Mean Low SD	-.014	.010	-.101	.165
Error Middle Low Mean Medium SD ↔ Error High Mean Low SD	-.041	.015	-.212	.007
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-.042	.016	-.230	.007
Error Middle High Mean Low SD ↔ Error Middle Low Mean Low SD	.028	.018	.136	.120
Error High Mean High SD ↔ Error Middle High Mean Low SD	.020	.009	.169	.027
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Low SD	-.063	.025	-.309	.012
Error Middle High Mean High SD ↔ Error Low Mean High SD	.022	.015	.126	.136
Error Low Mean High SD ↔ Error Low Mean Low SD	-.030	.012	-.231	.011

Table 41. Variances SEM Model 5

	Estimate	Standard Error	*p*
Conscientiousness Scale Sum	41.729	4.122	< .001
Emotional Stability Scale Sum	64.181	6.339	< .001
Extraversion Scale Sum	75.948	7.502	< .001
Error High Mean	.001	.002	.690
Error Middle High Mean	.041	.015	.008
Error Middle Low Mean	.137	.036	< .001
Error Low Mean	.024	.012	.043
Error High Mean High SD	.071	.010	< .001
Error Middle High Mean High SD	.250	.033	< .001
Error Middle Low Mean High SD	.251	.027	< .001
Error Low Mean High SD	.127	.018	< .001
Error High Mean Medium SD	.100	.012	< .001
Error Middle High Mean Medium SD	.195	.045	< .001
Error Middle Low Mean Medium SD	.241	.038	< .001
Error Low Mean Medium SD	.080	.014	< .001
Error High Mean Low SD	.158	.016	< .001
Error Middle High Mean Low SD	.203	.022	< .001
Error Middle Low Mean Low SD	.211	.033	< .001
Error Low Mean Low SD	.138	.017	< .001

Table 42. Squared Multiple Correlations SEM Model 5

Factor	Estimate
Low Mean Category	.110
Middle Low Mean Category	.041
Middle High Mean Category	.024
High Mean Category	.204
d’ Low Mean Low SD	.162
d’ Middle Low Mean Low SD	.405
d’ Middle High Mean Low SD	.172
d’ High Mean Low SD	.006
d’ Low Mean Medium SD	.384
d’ Middle Low Mean Medium SD	.428
d’ Middle High Mean Medium SD	.607
d’ High Mean Medium SD	.098
d’ Low Mean High SD	.263
d’ Middle Low Mean High SD	.183
d’ Middle High Mean High SD	.392
d’ High Mean High SD	.145

SEM Model 6: Analysis of Response Bias Across Personality Traits in Experiment 1

Table 43. Regression Weights for SEM Model 6

Path	Estimate	Standardized Estimate	Standard Error	*p*
Extraversion → High Mean Category	< .001	-.051	.001	.579
Extraversion → Middle High Mean Category	-.001	-.044	.002	.557
Extraversion → Middle Low Mean Category	-.002	-.047	.004	.536
Extraversion → Low Mean Category	-.002	-.067	.002	.392
Emotional Stability → High Mean Category	-.001	-.133	.001	.176
Emotional Stability → Middle High Mean Category	< .001	.001	.003	.994
Emotional Stability → Middle Low Mean Category	.007	.130	.004	.088
Emotional Stability → Low Mean Category	.004	.148	.002	.067
Conscientiousness → High Mean Category	< .001	.011	.001	.906
Conscientiousness → Middle High Mean Category	.001	.033	.003	.652
Conscientiousness → Middle Low Mean Category	.001	.007	.005	.923
Conscientiousness → Low Mean Category	< .001	.009	.002	.904
High Mean Category → *c* High Mean Low SD	1.000	.265		
High Mean Category → *c* High Mean Medium SD	3.704	.667	1.225	.002
High Mean Category → *c* High Mean High SD	2.068	.428	.708	.003
Middle High Mean Category → *c* Middle High Mean Low SD	1.000	.525		
Middle High Mean Category → *c* Middle High Mean Medium SD	1.763	.887	.313	< .001
Middle High Mean Category → *c* Middle High Mean High SD	1.155	.590	.168	< .001
Middle Low Mean Category → *c* Middle Low Mean High SD	.781	.624	.092	< .001
Middle Low Mean Category → *c* Middle Low Mean Medium SD	1.148	.851	.123	< .001
Middle Low Mean Category → *c* Middle Low Mean Low SD	1.000	.749		
Low Mean Category → *c* Low Mean Low SD	1.000	.497		
Low Mean Category → *c* Low Mean Medium SD	1.873	.718	.314	< .001
Low Mean Category → *c* Low Mean High SD	2.598	.778	.428	< .001

Table 44. Covariances SEM Model 6

Path	Covariance Estimate	Correlation Estimate	Standard Error	p
Error High Mean ↔ Error Middle High Mean	.016	.690	.006	.004
Error High Mean ↔ Error Middle Low Mean	.018	.479	.006	.006
Error Middle High Mean ↔ Error Middle Low Mean	.082	.635	.018	< .001
Error Middle High Mean ↔ Error Low Mean	.024	.420	.007	< .001
Error Middle Low Mean ↔ Error Low Mean	.073	.821	.015	< .001
Error Middle Low Mean Low SD ↔ Error Middle Low Mean Low SD	.023	.167	.012	.051
Error Middle Low Mean Medium SD ↔ Error Low Mean Medium SD	-.002	-.021	.017	.887
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Medium SD	.019	.220	.017	.261
Error High Mean Medium SD ↔ Error Middle High Mean Low SD	.013	.080	.014	.368
Error High Mean Medium SD ↔ Error Middle Low Mean Low SD	-.062	-.452	.015	< .001
Error High Mean Medium SD ↔ Error Middle High Mean Medium SD	.008	.088	.022	.718
Error Low Mean High SD ↔ Error Middle Low Mean Low SD	.061	.364	.018	< .001
Error Low Mean High SD ↔ Error Middle High Mean Medium SD	.036	.325	.017	.035
Error Middle Low Mean High SD ↔ Error Middle High Mean Low SD	.070	.338	.018	< .001
Error Middle Low Mean High SD ↔ Error Low Mean High SD	.051	.273	.016	.002
Error Middle High Mean High SD ↔ Error Low Mean High SD	.065	.341	.017	< .001
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.098	.484	.019	< .001
Error High Mean High SD ↔ Error Middle High Mean Low SD	.056	.332	.014	< .001
Error High Mean High SD ↔ Error Middle Low Mean Medium SD	-.036	-.314	.014	.010
Error High Mean High SD ↔ Error Middle Low Mean High SD	.027	.170	.015	.061
Error High Mean High SD ↔ Error Middle High Mean High SD	.066	.401	.015	< .001
Error Middle Low Mean High SD ↔	< .001	.001	.015	.996

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error High Mean Medium SD				
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-.024	-.213	.012	.052
Error Middle Low Mean High SD ↔ Error Middle High Mean Medium SD	.061	.520	.018	< .001
Error Middle High Mean High SD ↔ Error Middle High Mean Low SD	.049	.233	.020	.013
Error High Mean High SD ↔ Error Low Mean Low SD	-.020	-.159	.009	.025
Error High Mean High SD ↔ Error Middle Low Mean Low SD	-.045	-.312	.015	.002
Error High Mean High SD ↔ Error Low Mean High SD	.016	.105	.014	.246
Error Low Mean High SD ↔ Error High Mean Medium SD	.028	.199	.016	.076

Table 45. Variances SEM Model 6

	Estimate	Standard Error	*p*
Extraversion Scale Sum	75.948	7.502	< .001
Emotional Stability Scale Sum	64.181	6.339	< .001
Conscientiousness Scale Sum	41.729	4.122	< .001
Error High Mean	.007	.004	.080
Error Middle High Mean	.082	.024	< .001
Error Middle Low Mean	.204	.036	< .001
Error Low Mean	.038	.012	< .001
Error High Mean High SD	.129	.015	< .001
Error Middle High Mean High SD	.206	.026	< .001
Error Middle Low Mean High SD	.199	.023	< .001
Error Low Mean High SD	.174	.031	< .001
Error High Mean Medium SD	.116	.029	< .001
Error Middle High Mean Medium SD	.070	.035	.048
Error Middle Low Mean Medium SD	.104	.026	< .001
Error Low Mean Medium SD	.130	.021	< .001
Error High Mean Low SD	.090	.009	< .001
Error Middle High Mean Low SD	.218	.025	< .001
Error Middle Low Mean Low SD	.163	.024	< .001
Error Low Mean Low SD	.120	.013	< .001

Table 46. Squared Multiple Correlations SEM Model 6

Factor	Estimate
Low Mean Category	.027
Middle Low Mean Category	.019
Middle High Mean Category	.003
High Mean Category	.020
c Low Mean Low SD	.247
c Middle Low Mean Low SD	.561
c Middle High Mean Low SD	.275
c High Mean Low SD	.070
c Low Mean Medium SD	.516
c Middle Low Mean Medium SD	.725
c Middle High Mean Medium SD	.786
c High Mean Medium SD	.445
c Low Mean High SD	.605
c Middle Low Mean High SD	.390
c Middle High Mean High SD	.348
c High Mean High SD	.183

SEM Model 7: Analysis of Response Time Across Personality Traits in Experiment 1

Table 47. Regression Weights for SEM Model 7

Path	Estimate	Standardized Estimate	Standard Error	*p*
Extraversion Scale Sum → High Mean Category	-4.606	-.335	1.595	.004
Extraversion Scale Sum → Middle High Mean Category	-10.433	-.606	2.219	< .001
Extraversion Scale Sum → Middle Low Mean Category	-12.138	-.383	4.000	.002
Extraversion Scale Sum → Low Mean Category	-8.785	-.417	2.284	< .001
Emotional Stability Scale Sum → High Mean Category	3.367	.225	1.610	.036
Emotional Stability Scale Sum → Middle High Mean Category	6.408	.342	2.134	.003
Emotional Stability Scale Sum → Middle Low Mean Category	7.037	.204	4.088	.085
Emotional Stability Scale Sum → Low Mean Category	3.907	.170	2.425	.107
Conscientiousness Scale Sum → Low Mean Category	4.964	.174	3.016	.100
Conscientiousness Scale Sum → Middle Low Mean Category	2.113	.049	4.962	.670
Conscientiousness Scale Sum → Middle High Mean Category	5.777	.249	2.576	.025
Conscientiousness Scale Sum → High Mean Category	5.114	.276	2.058	.013
High Mean Category → Median *RT* High Mean Low SD	1.000	.448		
High Mean Category → Median *RT* High Mean Medium SD	1.042	.432	.292	< .001
High Mean Category → Median *RT* High Mean High SD	.948	.422	.276	< .001
Middle High Mean Category → Median *RT* Middle High Mean High SD	.772	.248	.249	.002
Middle High Mean Category → Median *RT* Middle High Mean Medium SD	.979	.376	.246	< .001
Middle High Mean Category → Median *RT* Middle High Mean Low SD	1.000	.441		
Middle Low Mean Category → Median *RT* Middle Low Mean High SD	.286	.155	.181	.114
Middle Low Mean Category → Median *RT* Middle Low Mean Medium SD	.720	.309	.314	.022

Path	Estimate	Standardized Estimate	Standard Error	*p*
Middle Low Mean Category → Median *RT* Middle Low Mean Low SD	1.000	.488		
Low Mean Category → Median *RT* Low Mean High SD	.406	.151	.268	.130
Low Mean Category → Median *RT* Low Mean Medium SD	.516	.205	.286	.071
Low Mean Category → Median *RT* Low Mean Low SD	1.000	.563		

Table 48. Covariances SEM Model 7

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle Low Mean Low SD ↔ Error Low Mean Low SD	80853.735	.607	13199.861	< .001
Error Middle High Mean Low SD ↔ Error Low Mean Low SD	47646.386	.579	7606.855	< .001
Error Middle High Mean Low SD ↔ Error Middle Low Mean Low SD	81467.508	.540	13299.474	< .001
Error High Mean Low SD ↔ Error Low Mean Low SD	42784.967	.665	6217.472	< .001
Error High Mean Low SD ↔ Error Middle Low Mean Low SD	59142.212	.502	10613.426	< .001
Error High Mean Low SD ↔ Error Middle High Mean Low SD	48898.179	.672	6575.972	< .001
Error Low Mean Medium SD ↔ Error Middle Low Mean Low SD	2274.723	.010	12965.027	.861
Error Low Mean Medium SD ↔ Error High Mean Low SD	4498.287	.042	6253.127	.472
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-4005.860	-.024	10420.140	.701
Error Middle Low Mean Medium SD ↔ Error High Mean Low SD	-7423.043	-.051	8726.644	.395
Error Middle High Mean Medium SD ↔ Error Low Mean Low SD	-2584.636	-.026	5703.030	.650
Error Middle High Mean Medium SD ↔ Error High Mean Low SD	-1382.660	-.016	5288.766	.794
Error Middle High Mean Medium SD ↔ Error Low Mean Medium SD	84214.949	.514	13312.331	< .001
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Medium SD	140403.396	.633	19170.168	< .001
Error High Mean Medium SD ↔ Error Middle High Mean Low SD	10646.694	.134	4266.076	.013
Error High Mean Medium SD ↔ Error	60039.117	.509	9709.681	< .001

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Low Mean Medium SD				
Error High Mean Medium SD ↔ Error Middle Low Mean Medium SD	85297.883	.534	13422.234	< .001
Error High Mean Medium SD ↔ Error Middle High Mean Medium SD	60523.400	.642	8320.699	< .001
Error Low Mean High SD ↔ Error High Mean Medium SD	-14245.276	-.112	6433.216	.027
Error Middle Low Mean High SD ↔ Error Low Mean Low SD	-13600.226	-.100	7170.461	.058
Error Middle Low Mean High SD ↔ Error Low Mean High SD	122777.062	.497	19320.601	< .001
Error Middle High Mean High SD ↔ Error Middle Low Mean Low SD	-7008.154	-.031	12023.558	.560
Error Middle High Mean High SD ↔ Error Low Mean Medium SD	14453.744	.071	9472.028	.127
Error Middle High Mean High SD ↔ Error Middle Low Mean Medium SD	5176.932	.019	12793.323	.686
Error Middle High Mean High SD ↔ Error High Mean Medium SD	-234.870	-.002	5929.519	.968
Error Middle High Mean High SD ↔ Error Low Mean High SD	123403.831	.559	17761.843	< .001
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	135838.962	.596	18671.809	< .001
Error High Mean High SD ↔ Error Middle Low Mean Low SD	-15704.427	-.131	7350.055	.033
Error High Mean High SD ↔ Error Middle High Mean Medium SD	4158.897	.047	4541.070	.360
Error High Mean High SD ↔ Error Low Mean High SD	52019.559	.437	9453.912	< .001
Error High Mean High SD ↔ Error Middle Low Mean High SD	53466.507	.435	9723.525	< .001
Error High Mean High SD ↔ Error Middle High Mean High SD	59175.545	.538	9142.405	< .001
Error Middle Low Mean Medium SD ↔ Error Low Mean Medium SD	194622.662	.701	24503.704	< .001

Table 49. Variances SEM Model 7

	Estimate	Standard Error	*p*
Extraversion Scale Sum	75.948	7.502	< .001
Emotional Stability Scale Sum	64.181	6.339	< .001
Conscientiousness Scale Sum	41.729	4.122	< .001
Error High Mean	10884.563	4321.525	.012
Error Middle High Mean	10200.800	5438.695	.061
Error Middle Low Mean	61814.086	34974.639	.077
Error Low Mean	25909.625	18124.614	.153
Error High Mean High SD	59282.592	6895.131	< .001
Error Middle High Mean High SD	203786.943	20743.908	< .001
Error Middle Low Mean High SD	254568.750	25583.094	< .001
Error Low Mean High SD	239324.108	23952.575	< .001
Error High Mean Medium SD	67887.956	8147.535	< .001
Error Middle High Mean Medium SD	130989.067	14347.045	< .001
Error Middle Low Mean Medium SD	375663.966	42244.236	< .001
Error Low Mean Medium SD	204978.579	21053.192	< .001
Error High Mean Low SD	56894.152	7098.329	< .001
Error Middle High Mean Low SD	93195.562	10841.150	< .001
Error Middle Low Mean Low SD	243830.232	42388.540	< .001
Error Low Mean Low SD	72747.179	19614.242	< .001

Table 50. Squared Multiple Correlations SEM Model 7

Factor	Estimate
Low Mean Category	.233
Middle Low Mean Category	.191
Middle High Mean Category	.547
High Mean Category	.240
Median *RT* Low Mean Low SD	.317
Median *RT* Middle Low Mean Low SD	.239
Median *RT* Middle High Mean Low SD	.194
Median *RT* High Mean Low SD	.201
Median *RT* Low Mean Medium SD	.042
Median *RT* Middle Low Mean Medium SD	.095
Median *RT* Middle High Mean Medium SD	.141
Median *RT* High Mean Medium SD	.186
Median *RT* Low Mean High SD	.023
Median *RT* Middle Low Mean High SD	.024
Median *RT* Middle High Mean High SD	.062
Median *RT* High Mean High SD	.178

SEM Model 8: SEM Analysis of Extraversion Interacting with Cognitive Skills for *d'* in Experiment 1

Table 51. Regression Weights for SEM Model 8

Path	Estimate	Standardized Estimate	Standard Error	*p*
Cognitive Skills x Extraversion → Low Mean Category	< .001	-.044	< .001	.630
Cognitive Skills x Extraversion → Middle Low Mean Category	< .001	-.045	< .001	.585
Cognitive Skills x Extraversion → Middle High Mean Category	< .001	-.066	< .001	.414
Cognitive Skills x Extraversion → High Mean Category	< .001	-.071	< .001	.646
Cognitive Skills (Mean Centered) → Low Mean Category	.002	.193	.001	.059
Cognitive Skills (Mean Centered) → Middle Low Mean Category	.009	.399	.002	< .001
Cognitive Skills (Mean Centered) → Middle High Mean Category	.004	.327	.001	< .001
Cognitive Skills (Mean Centered) → High Mean Category	< .001	.151	< .001	.452
Extraversion (Mean Centered) → Low Mean Category	-.004	-.198	.002	.054
Extraversion (Mean Centered) → Middle Low Mean Category	-.002	-.042	.004	.606
Extraversion (Mean Centered) → Middle High Mean Category	-.001	-.041	.002	.610
Extraversion (Mean Centered) → High Mean Category	-.002	-.331	.002	.341
High Mean Category → *d'* High Mean Low SD	1.000	.100		
High Mean Category → *d'* High Mean Medium SD	2.089	.248	2.192	.340
High Mean Category → *d'* High Mean High SD	3.209	.443	3.219	.319
Middle High Mean Category → *d'* Middle High Mean Low SD	1.869	.630	.379	< .001
Middle High Mean Category → *d'* Middle High Mean Medium SD	2.470	.759	.501	< .001
Middle High Mean Category → *d'* Middle High Mean High SD	1.000	.435		
Middle Low Mean Category → *d'* Middle Low Mean High SD	.582	.426	.125	< .001

Path	Estimate	Standardized Estimate	Standard Error	p
Middle Low Mean Category → *d'* Middle Low Mean Medium SD	.977	.611	.175	< .001
Middle Low Mean Category → *d'* Middle Low Mean Low SD	1.000	.683		
Low Mean Category → *d'* Low Mean High SD	1.275	.477	.413	.002
Low Mean Category → *d'* Low Mean Medium SD	1.514	.652	.510	.003
Low Mean Category → *d'* Low Mean Low SD	1.000	.382		

Table 52. Covariances SEM Model 8

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle Low Mean ↔ Error Low Mean	.022	.396	.009	.014
Error High Mean ↔ Error Middle Low Mean	.003	.253	.004	.407
Error Middle High Mean ↔ Error Middle Low Mean	.049	.645	.014	< .001
Error Middle High Mean ↔ Error Low Mean	.011	.368	.005	.020
Error High Mean ↔ Error Middle High Mean	.005	.687	.005	.326
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.078	.314	.021	< .001
Error Middle Low Mean High SD ↔ Error Low Mean High SD	.037	.202	.014	.010
Error Low Mean High SD ↔ Error High Mean Medium SD	-.017	-.147	.009	.051
Error Low Mean High SD ↔ Error High Mean Low SD	-.015	-.105	.010	.144
Error Middle Low Mean Medium SD ↔ Error High Mean Low SD	-.039	-.194	.016	.011
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-.043	-.222	.016	.006
Error Middle High Mean Low SD ↔ Error Middle Low Mean Low SD	.020	.102	.018	.267
Error High Mean High SD ↔ Error Middle High Mean Low SD	.019	.163	.009	.042
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Low SD	-.069	-.348	.024	.004
Error Middle High Mean High SD ↔ Error Low Mean High SD	.024	.131	.015	.115
Error Low Mean High SD ↔ Error Low Mean Low SD	-.026	-.194	.012	.031

Table 53. Variances SEM Model 8

	Estimate	Standard Error	*p*
Cognitive Skills x Extraversion	23403.643	2311.647	< .001
Cognitive Skills (Mean Centered)	323.634	31.966	< .001
Extraversion (Mean Centered)	75.948	7.502	< .001
Error High Mean	.001	.003	.612
Error Middle High Mean	.041	.015	.006
Error Middle Low Mean	.138	.035	< .001
Error Low Mean	.022	.012	.056
Error High Mean High SD	.066	.012	< .001
Error Middle High Mean High SD	.247	.032	< .001
Error Middle Low Mean High SD	.251	.027	< .001
Error Low Mean High SD	.132	.018	< .001
Error High Mean Medium SD	.104	.011	< .001
Error Middle High Mean Medium SD	.209	.043	< .001
Error Middle Low Mean Medium SD	.264	.036	< .001
Error Low Mean Medium SD	.074	.016	< .001
Error High Mean Low SD	.157	.016	< .001
Error Middle High Mean Low SD	.199	.022	< .001
Error Middle Low Mean Low SD	.188	.033	< .001
Error Low Mean Low SD	.140	.017	<.001

Table 54. Squared Multiple Correlations SEM Model 8

Factor	Estimate
Low Mean Category	.079
Middle Low Mean Category	.163
Middle High Mean Category	.113
High Mean Category	.138
d' Low Mean Low SD	.146
d' Middle Low Mean Low SD	.467
d' Middle High Mean Low SD	.189
d' High Mean Low SD	.010
d' Low Mean Medium SD	.425
d' Middle Low Mean Medium SD	.373
d' Middle High Mean Medium SD	.576
d' High Mean Medium SD	.062
d' Low Mean High SD	.227
d' Middle Low Mean High SD	.182
d' Middle High Mean High SD	.397
d' High Mean High SD	.196

SEM Model 9: SEM Model Analysis of Cognitive Skills Interacting with Extraversion for Index *c* in Experiment 1

Table 55. Regression Weights for SEM Model 9

Path	Estimate	Standardized Estimate	Standard Error	*p*
Extraversion (Mean Centered) → High Mean Category	-.001	-.058	.001	.524
Extraversion (Mean Centered) → Middle High Mean Category	< .001	-.009	.002	.898
Extraversion (Mean Centered) → Middle Low Mean Category	.001	.026	.004	.720
Extraversion (Mean Centered) → Low Mean Category	< .001	.005	.002	.942
Cognitive Skills (Mean Centered) → High Mean Category	.001	.133	< .001	.175
Cognitive Skills (Mean Centered) → Middle High Mean Category	.003	.212	.001	.008
Cognitive Skills (Mean Centered) → Middle Low Mean Category	.009	.345	.002	< .001
Cognitive Skills (Mean Centered) → Low Mean Category	.004	.387	.001	< .001
Cognitive Skills x Extraversion → High Mean Category	< .001	.027	< .001	.765
Cognitive Skills x Extraversion → Middle High Mean Category	< .001	-.036	< .001	.622
Cognitive Skills x Extraversion → Middle Low Mean Category	< .001	-.047	< .001	.518
Cognitive Skills x Extraversion → Low Mean Category	< .001	.039	< .001	.604
High Mean Category → *c* High Mean Low SD	1.000	.272		
High Mean Category → *c* High Mean Medium SD	3.688	.682	1.218	.002
High Mean Category → *c* High Mean High SD	1.962	.417	.668	.003
Middle High Mean Category → *c* Middle High Mean Low SD	1.000	.531		
Middle High Mean Category → *c* Middle High Mean Medium SD	1.739	.883	.300	< .001
Middle High Mean Category → *c* Middle High Mean High SD	1.150	.594	.165	< .001
Middle Low Mean Category → *c* Middle Low Mean High SD	.762	.628	.089	< .001

Path	Estimate	Standardized Estimate	Standard Error	*p*
Middle Low Mean Category → *c* Middle Low Mean Medium SD	1.081	.826	.110	< .001
Middle Low Mean Category → *c* Middle Low Mean Low SD	1.000	.775		
Low Mean Category → *c* Low Mean Low SD	1.000	.500		
Low Mean Category → *c* Low Mean Medium SD	1.812	.696	.299	< .001
Low Mean Category → *c* Low Mean High SD	2.659	.797	.428	< .001

Table 56. Covariances SEM Model 9

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error High Mean ↔ Error Middle High Mean	.016	.682	.006	.004
Error High Mean ↔ Error Middle Low Mean	.018	.475	.006	.006
Error Middle High Mean ↔ Error Middle Low Mean	.078	.622	.017	< .001
Error Middle High Mean ↔ Error Low Mean	.022	.417	.006	< .001
Error Middle Low Mean ↔ Error Low Mean	.066	.815	.014	< .001
Error Middle Low Mean Low SD ↔ Error Low Mean Low SD	.018	.133	.012	.134
Error Middle Low Mean Medium SD ↔ Error Low Mean Medium SD	.010	.075	.016	.535
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Medium SD	.023	.248	.016	.143
Error High Mean Medium SD ↔ Error Middle High Mean Low SD	.013	.086	.014	.344
Error High Mean Medium SD ↔ Error Middle Low Mean Low SD	-.065	-.505	.015	< .001
Error High Mean Medium SD ↔ Error Middle High Mean Medium SD	.007	.079	.022	.743
Error Low Mean High SD ↔ Error Middle Low Mean Low SD	.047	.306	.018	.008
Error Low Mean High SD ↔ Error Middle High Mean Medium SD	.030	.281	.017	.072
Error Middle Low Mean High SD ↔ Error Middle High Mean Low SD	.070	.335	.018	< .001
Error Middle Low Mean High SD ↔	.048	.269	.016	.003

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Low Mean High SD				
Error Middle High Mean High SD ↔ Error Low Mean High SD	.059	.325	.017	< .001
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.097	.479	.019	< .001
Error High Mean High SD ↔ Error Middle High Mean Low SD	.058	.342	.014	< .001
Error High Mean High SD ↔ Error Middle Low Mean Medium SD	-.033	-.261	.014	.015
Error High Mean High SD ↔ Error Middle Low Mean High SD	.029	.176	.014	.048
Error High Mean High SD ↔ Error Middle High Mean High SD	.066	.402	.015	< .001
Error Middle Low Mean High SD ↔ Error High Mean Medium SD	-.003	-.021	.015	.833
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-.023	-.189	.012	.055
Error Middle Low Mean High SD ↔ Error Middle High Mean Medium SD	.060	.500	.018	< .001
Error Middle High Mean High SD ↔ Error Middle High Mean Low SD	.050	.235	.020	.011
Error High Mean High SD ↔ Error Low Mean Low SD	-.019	-.150	.009	.033
Error High Mean High SD ↔ Error Middle .Low Mean Low SD	-.042	-.298	.014	.004
Error High Mean High SD ↔ Error Low Mean High SD	.017	.116	.013	.212
Error Low Mean High SD ↔ Error High Mean Medium SD	.023	.174	.016	.136

Table 57. Variances SEM Model 9

	Estimate	Standard Error	*p*
Extraversion (Mean Centered)	75.948	7.502	< .001
Cognitive Skills (Mean Centered)	323.634	31.966	< .001
Cognitive Skills x Extraversion	23403.643	2311.647	< .001
Error High Mean	.007	.004	.075
Error Middle High Mean	.081	.023	< .001
Error Middle Low Mean	.196	.034	< .001
Error Low Mean	.034	.010	< .001
Error High Mean High SD	.131	.015	< .001
Error Middle High Mean High SD	.206	.026	< .001
Error Middle Low Mean High SD	.200	.023	< .001
Error Low Mean High SD	.161	.030	< .001
Error High Mean Medium SD	.112	.030	< .001
Error Middle High Mean Medium SD	.073	.034	.031
Error Middle Low Mean Medium SD	.122	.024	< .001
Error Low Mean Medium SD	.139	.019	< .001
Error High Mean Low SD	.089	.009	< .001
Error Middle High Mean Low SD	.217	.025	< .001
Error Middle Low Mean Low SD	.148	.023	< .001
Error Low Mean Low SD	.119	.013	<.001

Table 58. Squared Multiple Correlations SEM Model 9

Factor	Estimate
Low Mean Category	.152
Middle Low Mean Category	.122
Middle High Mean Category	.046
High Mean Category	.022
c Low Mean Low SD	.250
c Middle Low Mean Low SD	.601
c Middle High Mean Low SD	.282
c High Mean Low SD	.074
c Low Mean Medium SD	.484
c Middle Low Mean Medium SD	.682
c Middle High Mean Medium SD	.779
c High Mean Medium SD	.465
c Low Mean High SD	.635
c Middle Low Mean High SD	.394
c Middle High Mean High SD	.353
c High Mean High SD	.173

SEM Model 10: Path Analysis of Cognitive Skills Interacting with Extraversion for Response Time in Experiment 1

Table 59. Regression Weights for SEM Model 10

Path	Estimate	Standardized Estimate	Standard Error	*p*
Extraversion (Mean Centered) → High Mean Category	-1.598	-.144	.763	.036
Extraversion (Mean Centered) → Middle High Mean Category	-2.621	-.181	.993	.008
Extraversion (Mean Centered) → Middle Low Mean Category	-2.445	-.162	1.037	.018
Extraversion (Mean Centered) → Low Mean Category	-1.830	-.175	.719	.011
Cognitive Skills (Mean Centered) → High Mean Category	-.426	-.079	.370	.250
Cognitive Skills (Mean Centered) → Middle High Mean Category	.159	.023	.481	.741
Cognitive Skills (Mean Centered) → Middle Low Mean Category	.174	.024	.502	.730
Cognitive Skills (Mean Centered) → Low Mean Category	.089	.018	.348	.799
Cognitive Skills x Extraversion → Low Mean Category	.021	.035	.041	.611
Cognitive Skills x Extraversion → Middle Low Mean Category	.022	.026	.059	.706
Cognitive Skills x Extraversion → Middle High Mean Category	.029	.035	.057	.608
Cognitive Skills x Extraversion → High Mean Category	.005	.008	.043	.907

Table 60. Covariances SEM Model 10

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle High Mean ↔ Error Low Mean	11054.298	.995	1094.872	< .001
Error Middle Low Mean ↔ Error Low Mean	11389.063	.981	1136.048	< .001
Error Middle High Mean ↔ Error Middle Low Mean	15589.273	.973	1561.486	< .001
Error High Mean ↔ Error Low Mean	6982.046	.817	770.898	< .001
Error High Mean ↔ Error Middle Low Mean	10036.867	.814	1110.150	< .001
Error High Mean ↔ Error Middle High Mean	9986.598	.847	1079.507	< .001

Table 61. Variances SEM Model 10

	Estimate	Standard Error	*p*
Extraversion (Mean Centered)	75.948	7.502	< .001
Cognitive Skills (Mean Centered)	323.634	31.966	<.001
Cognitive Skills x Extraversion	23403.643	2311.647	<.001
Error High Mean	9072.846	896.152	<.001
Error Middle High Mean	15338.235	1515.003	<.001
Error Middle Low Mean	16743.360	1653.791	< .001
Error Low Mean	8054.722	795.589	<.001

Table 62. Squared Multiple Correlations SEM Model 10

Factor	Estimate
Low Mean Category	.032
Middle Low Mean Category	.028
Middle High Mean Category	.035
High Mean Category	.027

SEM Model 11: SEM Analysis of Emotional Stability Interacting with Cognitive Skills for *d'* in Experiment 1

Table 63. Regression Weights for SEM Model 11

Path	Estimate	Standardized Estimate	Standard Error	*p*
Cognitive Skills x Emotional Stability → Low Mean Category	< .001	-.088	< .001	.344
Cognitive Skills x Emotional Stability → Middle Low Mean Category	< .001	-.142	< .001	.077
Cognitive Skills x Emotional Stability → Middle High Mean Category	< .001	-.108	< .001	.186
Cognitive Skills x Emotional Stability → High Mean Category	< .001	.347	< .001	.700
Cognitive Skills (Mean Centered) → Low Mean Category	.002	.211	.001	.049
Cognitive Skills (Mean Centered) → Middle Low Mean Category	.010	.416	.002	< .001
Cognitive Skills (Mean Centered) → Middle High Mean Category	.004	.339	.001	< .001
Cognitive Skills (Mean Centered) → High Mean Category	< .001	.149	< .001	.713
Emotional Stability (Mean Centered) → Low Mean Category	-.001	-.060	.002	.508
Emotional Stability (Mean Centered) → Middle Low Mean Category	.008	.145	.004	.070
Emotional Stability (Mean Centered) → Middle High Mean Category	.001	.050	.002	.530
Emotional Stability (Mean Centered) → High Mean Category	-.001	-.295	.001	.702
High Mean Category → *d'* High Mean Low SD	1.000	.034		
High Mean Category → *d'* High Mean Medium SD	6.463	.262	16.791	.700
High Mean Category → *d'* High Mean High SD	9.728	.457	25.107	.698
Middle High Mean Category → *d'* Middle High Mean High SD	1.872	.632	.378	< .001
Middle High Mean Category → *d'* Middle High Mean Medium SD	2.458	.756	.497	< .001
Middle High Mean Category → *d'* Middle High Mean Low SD	1.000	.435		
Middle Low Mean Category → *d'* Middle Low Mean High SD	.568	.425	.118	< .001

Path	Estimate	Standardized Estimate	Standard Error	*p*
Middle Low Mean Category → *d'* Middle Low Mean Medium SD	.964	.611	.162	< .001
Middle Low Mean Category → *d'* Middle Low Mean Low SD	1.000	.695		
Low Mean Category → *d'* Low Mean High SD	1.322	.466	.437	.002
Low Mean Category → *d'* Low Mean Medium SD	1.677	.681	.598	.005
Low Mean Category → *d'* Low Mean Low SD	1.000	.361		

Table 64. Covariances SEM Model 11

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle Low Mean ↔ Error Low Mean	.020	.391	.009	.017
Error High Mean ↔ Error Middle Low Mean	.002	.382	.004	.701
Error Middle High Mean ↔ Error Middle Low Mean	.048	.643	.014	< .001
Error Middle High Mean ↔ Error Low Mean	.010	.357	.005	.025
Error High Mean ↔ Error Middle High Mean	.002	.777	.005	.699
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.077	.310	.021	< .001
Error Middle Low Mean High SD ↔ Error Low Mean High SD	.037	.204	.014	.009
Error Low Mean High SD ↔ Error High Mean Medium SD	-.017	-.145	.009	.052
Error Low Mean High SD ↔ Error High Mean Low SD	-.014	-.097	.010	.170
Error Middle Low Mean Medium SD ↔ Error High Mean Low SD	-.040	-.195	.016	.010
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-.041	-.210	.016	.008
Error Middle High Mean Low SD ↔ Error Middle Low Mean Low SD	.021	.110	.018	.231
Error High Mean High SD ↔ Error Middle High Mean Low SD	.020	.171	.009	.031
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Low SD	-.069	-.350	.024	.004
Error Middle High Mean High SD ↔ Error Low Mean High SD	.024	.132	.015	.109
Error Low Mean High SD ↔ Error Low Mean Low SD	-.024	-.171	.012	.052

Table 65. Variances SEM Model 11

	Estimate	Standard Error	*p*
Cognitive Skills x Emotional Stability	18303.108	1807.852	< .001
Cognitive Skills (Mean Centered)	323.634	31.966	< .001
Emotional Stability (Mean Centered)	64.181	6.339	< .001
Error High Mean	< .001	.001	.847
Error Middle High Mean	.041	.015	.006
Error Middle Low Mean	.135	.033	< .001
Error Low Mean	.020	.011	.069
Error High Mean High SD	.066	.011	< .001
Error Middle High Mean High SD	.246	.032	< .001
Error Middle Low Mean High SD	.252	.027	< .001
Error Low Mean High SD	.135	.018	< .001
Error High Mean Medium SD	.104	.011	< .001
Error Middle High Mean Medium SD	.211	.043	< .001
Error Middle Low Mean Medium SD	.268	.035	< .001
Error Low Mean Medium SD	.069	.018	< .001
Error High Mean Low SD	.159	.016	< .001
Error Middle High Mean Low SD	.200	.022	< .001
Error Middle Low Mean Low SD	.184	.032	< .001
Error Low Mean Low SD	.142	.016	< .001

Table 66. Squared Multiple Correlations SEM Model 11

Factor	Estimate
Low Mean Category	.056
Middle Low Mean Category	.214
Middle High Mean Category	.129
High Mean Category	.230
d' Low Mean Low SD	.130
d' Middle Low Mean Low SD	.484
d' Middle High Mean Low SD	.190
d' High Mean Low SD	.001
d' Low Mean Medium SD	.464
d' Middle Low Mean Medium SD	.374
d' Middle High Mean Medium SD	.572
d' High Mean Medium SD	.069
d' Low Mean High SD	.217
d' Middle Low Mean High SD	.181
d' Middle High Mean High SD	.399
d' High Mean High SD	.209

SEM Model 12: SEM Model Analysis of Cognitive Skills Interacting with Emotional Stability for Index *c* in Experiment 1

Table 67. Regression Weights for SEM Model 12

Path	Estimate	Standardized Estimate	Standard Error	*p*
Emotional Stability (Mean Centered) → High Mean Category	-.001	-.127	.001	.186
Emotional Stability (Mean Centered) → Middle High Mean Category	.001	.037	.003	.614
Emotional Stability (Mean Centered) → Middle Low Mean Category	.011	.177	.004	.013
Emotional Stability (Mean Centered) → Low Mean Category	.005	.183	.002	.017
Cognitive Skills (Mean Centered) → High Mean Category	.001	.130	< .001	.182
Cognitive Skills (Mean Centered) → Middle High Mean Category	.004	.223	.001	.005
Cognitive Skills (Mean Centered) → Middle Low Mean Category	.010	.361	.002	< .001
Cognitive Skills (Mean Centered) → Low Mean Category	.005	.400	.001	< .001
Cognitive Skills x Emotional Stability → High Mean Category	< .001	-.018	< .001	.837
Cognitive Skills x Emotional Stability → Middle High Mean Category	< .001	-.150	< .001	.047
Cognitive Skills x Emotional Stability → Middle Low Mean Category	-.001	-.197	< .001	.006
Cognitive Skills x Emotional Stability → Low Mean Category	< .001	-.106	< .001	.151
High Mean Category → *c* High Mean Low SD	1.000	.267		
High Mean Category → *c* High Mean Medium SD	3.780	.686	1.243	.002
High Mean Category → *c* High Mean High SD	1.997	.416	.682	.003
Middle High Mean Category → *c* Middle High Mean Low SD	1.000	.534		
Middle High Mean Category → *c* Middle High Mean Medium SD	1.721	.878	.292	< .001
Middle High Mean Category → *c* Middle High Mean High SD	1.150	.598	.164	< .001
Middle Low Mean Category → *c* Middle Low Mean High SD	.763	.633	.088	< .001

Path	Estimate	Standardized Estimate	Standard Error	*p*
Middle Low Mean Category → *c* Middle Low Mean Medium SD	1.077	.827	.105	< .001
Middle Low Mean Category → *c* Middle Low Mean Low SD	1.000	.779		
Low Mean Category → *c* Low Mean Low SD	1.000	.508		
Low Mean Category → *c* Low Mean Medium SD	1.770	.690	.287	< .001
Low Mean Category → *c* Low Mean High SD	2.635	.801	.414	< .001

Table 68. Covariances SEM Model 12

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error High Mean ↔ Error Middle High Mean	.016	.695	.006	.004
Error High Mean ↔ Error Middle Low Mean	.017	.500	.006	.006
Error Middle High Mean ↔ Error Middle Low Mean	.075	.617	.016	< .001
Error Middle High Mean ↔ Error Low Mean	.021	.401	.006	< .001
Error Middle Low Mean ↔ Error Low Mean	.062	.804	.013	< .001
Error Middle Low Mean Low SD ↔ Error Low Mean Low SD	.015	.116	.012	.190
Error Middle Low Mean Medium SD ↔ Error Low Mean Medium SD	.012	.087	.015	.452
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Medium SD	.023	.242	.016	.137
Error High Mean Medium SD ↔ Error Middle High Mean Low SD	.012	.075	.014	.409
Error High Mean Medium SD ↔ Error Middle Low Mean Low SD	-.065	-.510	.015	< .001
Error High Mean Medium SD ↔ Error Middle High Mean Medium SD	.007	.076	.022	.749
Error Low Mean High SD ↔ Error Middle Low Mean Low SD	.047	.305	.017	.007
Error Low Mean High SD ↔ Error Middle High Mean Medium SD	.032	.294	.017	.056
Error Middle Low Mean High SD ↔ Error Middle High Mean Low SD	.070	.336	.018	< .001
Error Middle Low Mean High SD ↔	.048	.269	.016	.003

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Low Mean High SD				
Error Middle High Mean High SD ↔ Error Low Mean High SD	.060	.333	.017	< .001
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.097	.478	.019	< .001
Error High Mean High SD ↔ Error Middle High Mean Low SD	.057	.339	.014	< .001
Error High Mean High SD ↔ Error Middle Low Mean Medium SD	-.032	-.249	.013	.019
Error High Mean High SD ↔ Error Middle Low Mean High SD	.029	.181	.014	.042
Error High Mean High SD ↔ Error Middle High Mean High SD	.066	.403	.015	< .001
Error Middle Low Mean High SD ↔ Error High Mean Medium SD	-.002	-.014	.015	.890
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-.026	-.216	.012	.027
Error Middle Low Mean High SD ↔ Error Middle High Mean Medium SD	.061	.493	.018	< .001
Error Middle High Mean High SD ↔ Error Middle High Mean Low SD	.049	.231	.019	.013
Error High Mean High SD ↔ Error Low Mean Low SD	-.018	-.143	.009	.043
Error High Mean High SD ↔ Error Middle .Low Mean Low SD	-.040	-.289	.014	.005
Error High Mean High SD ↔ Error Low Mean High SD	.018	.125	.013	.179
Error Low Mean High SD ↔ Error High Mean Medium SD	.026	.198	.016	.090

Table 69. Variances SEM Model 12

	Estimate	Standard Error	*p*
Emotional Stability (Mean Centered)	64.181	6.339	< .001
Cognitive Skills (Mean Centered)	323.634	31.966	< .001
Cognitive Skills x Emotional Stability	18303.108	1807.852	< .001
Error High Mean	.007	.004	.077
Error Middle High Mean	.080	.022	< .001
Error Middle Low Mean	.183	.031	< .001
Error Low Mean	.033	.010	< .001
Error High Mean High SD	.131	.015	< .001
Error Middle High Mean High SD	.205	.026	< .001
Error Middle Low Mean High SD	.199	.022	< .001
Error Low Mean High SD	.159	.030	< .001
Error High Mean Medium SD	.111	.030	< .001
Error Middle High Mean Medium SD	.076	.033	.022
Error Middle Low Mean Medium SD	.123	.024	< .001
Error Low Mean Medium SD	.142	.019	< .001
Error High Mean Low SD	.090	.009	< .001
Error Middle High Mean Low SD	.216	.025	< .001
Error Middle Low Mean Low SD	.148	.022	< .001
Error Low Mean Low SD	.118	.013	< .001

Table 70. Squared Multiple Correlations SEM Model 12

Factor	Estimate
Low Mean Category	.205
Middle Low Mean Category	.201
Middle High Mean Category	.073
High Mean Category	.033
c Low Mean Low SD	.258
c Middle Low Mean Low SD	.607
c Middle High Mean Low SD	.285
c High Mean Low SD	.071
c Low Mean Medium SD	.476
c Middle Low Mean Medium SD	.683
c Middle High Mean Medium SD	.771
c High Mean Medium SD	.471
c Low Mean High SD	.642
c Middle Low Mean High SD	.400
c Middle High Mean High SD	.357
c High Mean High SD	.173

SEM Model 13: Path Analysis of Cognitive Skills Interacting with Emotional Stability for Response Time in Experiment 1

Table 71. Regression Weights for SEM Model 13

Path	Estimate	Standardized Estimate	Standard Error	*p*
Emotional Stability (Mean Centered) → High Mean Category	1.813	.150	.824	.028
Emotional Stability (Mean Centered) → Middle High Mean Category	2.373	.151	1.084	.029
Emotional Stability (Mean Centered) → Middle Low Mean Category	2.522	.154	1.127	.025
Emotional Stability (Mean Centered) → Low Mean Category	1.621	.142	.785	.039
Cognitive Skills (Mean Centered) → High Mean Category	-.276	-.051	.367	.451
Cognitive Skills (Mean Centered) → Middle High Mean Category	.363	.052	.483	.452
Cognitive Skills (Mean Centered) → Middle Low Mean Category	.378	.052	.502	.451
Cognitive Skills (Mean Centered) → Low Mean Category	.230	.045	.350	.511
Cognitive Skills x Emotional Stability → Low Mean Category	-.051	-.076	.047	.273
Cognitive Skills x Emotional Stability → Middle Low Mean Category	-.086	-.088	.067	.197
Cognitive Skills x Emotional Stability → Middle High Mean Category	-.074	-.079	.064	.252
Cognitive Skills x Emotional Stability → High Mean Category	-.101	-.141	.049	.039

Table 72. Covariances SEM Model 13

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle High Mean ↔ Error Low Mean	11139.069	.995	1103.235	< .001
Error Middle Low Mean ↔ Error Low Mean	11425.248	.981	1139.607	< .001
Error Middle High Mean ↔ Error Middle Low Mean	15632.753	.973	1565.914	< .001
Error High Mean ↔ Error Low Mean	6956.637	.817	767.744	< .001
Error High Mean ↔ Error Middle Low Mean	9939.411	.814	1099.799	< .001
Error High Mean ↔ Error Middle High Mean	9944.355	.847	1074.705	< .001

Table 73. Variances SEM Model 13

	Estimate	Standard Error	*p*
Emotional Stability (Mean Centered)	64.181	6.339	< .001
Cognitive Skills (Mean Centered)	323.634	31.966	< .001
Cognitive Skills x Emotional Stability	18303.108	1807.852	< .001
Error High Mean	8923.490	881.399	< .001
Error Middle High Mean	15451.687	1526.209	< .001
Error Middle Low Mean	16716.283	1651.117	< .001
Error Low Mean	8117.718	801.811	< .001

Table 74. Squared Multiple Correlations SEM Model 13

Factor	Estimate
Low Mean Category	.028
Middle Low Mean Category	.034
Middle High Mean Category	.032
High Mean Category	.045

SEM Model 14: SEM Analysis of Conscientiousness Interacting with Cognitive Skills for *d'* in Experiment 1

Table 75. Regression Weights for SEM Model 14

Path	Estimate	Standardized Estimate	Standard Error	*p*
Cognitive Skills x Conscientiousness → Low Mean Category	< .001	-.034	< .001	.704
Cognitive Skills x Conscientiousness → Middle Low Mean Category	-.001	-.223	< .001	.007
Cognitive Skills x Conscientiousness → Middle High Mean Category	< .001	.064	< .001	.417
Cognitive Skills x Conscientiousness → High Mean Category	< .001	.109	< .001	.585
Cognitive Skills (Mean Centered) → Low Mean Category	.002	.229	.001	.034
Cognitive Skills (Mean Centered) → Middle Low Mean Category	.009	.410	.002	< .001
Cognitive Skills (Mean Centered) → Middle High Mean Category	.004	.336	.001	< .001
Cognitive Skills (Mean Centered) → High Mean Category	< .001	.170	< .001	.524
Conscientiousness (Mean Centered) → Low Mean Category	.004	.158	.002	.109
Conscientiousness (Mean Centered) → Middle Low Mean Category	-.004	-.072	.005	.369
Conscientiousness (Mean Centered) → Middle High Mean Category	.004	.133	.003	.104
Conscientiousness (Mean Centered) → High Mean Category	< .001	.017	.001	.902
High Mean Category → *d'* High Mean Low SD	1.000	.077		
High Mean Category → *d'* High Mean Medium SD	2.642	.243	3.752	.481
High Mean Category → *d'* High Mean High SD	4.373	.467	6.060	.471
Middle High Mean Category → *d'* Middle High Mean High SD	1.889	.627	.383	< .001
Middle High Mean Category → *d'* Middle High Mean Medium SD	2.554	.770	.514	< .001
Middle High Mean Category → *d'* Middle High Mean Low SD	1.000	.429		
Middle Low Mean Category → *d'* Middle Low Mean High SD	.621	.435	.127	< .001

Path	Estimate	Standardized Estimate	Standard Error	*p*
Middle Low Mean Category → *d'* Middle Low Mean Medium SD	1.077	.641	.178	< .001
Middle Low Mean Category → *d'* Middle Low Mean Low SD	1.000	.653		
Low Mean Category → *d'* Low Mean High SD	1.320	.473	.432	.002
Low Mean Category → *d'* Low Mean Medium SD	1.629	.672	.558	.004
Low Mean Category → *d'* Low Mean Low SD	1.000	.368		

Table 76. Covariances SEM Model 14

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle Low Mean ↔ Error Low Mean	.021	.420	.008	.014
Error High Mean ↔ Error Middle Low Mean	.003	.283	.004	.496
Error Middle High Mean ↔ Error Middle Low Mean	.047	.699	.013	< .001
Error Middle High Mean ↔ Error Low Mean	.010	.356	.004	.024
Error High Mean ↔ Error Middle High Mean	.004	.630	.005	.472
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.076	.306	.021	< .001
Error Middle Low Mean High SD ↔ Error Low Mean High SD	.037	.203	.014	.010
Error Low Mean High SD ↔ Error High Mean Medium SD	-.017	-.142	.009	.058
Error Low Mean High SD ↔ Error High Mean Low SD	-.015	-.101	.010	.157
Error Middle Low Mean Medium SD ↔ Error High Mean Low SD	-.041	-.206	.015	.008
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-.039	-.209	.015	.010
Error Middle High Mean Low SD ↔ Error Middle Low Mean Low SD	.023	.113	.018	.198
Error High Mean High SD ↔ Error Middle High Mean Low SD	.020	.178	.009	.029
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Low SD	-.065	-.320	.024	.006
Error Middle High Mean High SD ↔ Error Low Mean High SD	.023	.128	.015	.117
Error Low Mean High SD ↔ Error Low Mean Low SD	-.025	-.180	.012	.041

Table 77. Variances SEM Model 14

	Estimate	Standard Error	p
Cognitive Skills x Conscientiousness	16953.833	1674.580	< .001
Cognitive Skills (Mean Centered)	323.634	31.966	< .001
Conscientiousness (Mean Centered)	41.729	4.122	< .001
Error High Mean	.001	.002	.711
Error Middle High Mean	.039	.014	.006
Error Middle Low Mean	.117	.030	< .001
Error Low Mean	.020	.011	.063
Error High Mean High SD	.065	.013	< .001
Error Middle High Mean High SD	.249	.032	< .001
Error Middle Low Mean High SD	.248	.027	< .001
Error Low Mean High SD	.134	.018	< .001
Error High Mean Medium SD	.105	.011	< .001
Error Middle High Mean Medium SD	.203	.043	< .001
Error Middle Low Mean Medium SD	.251	.035	< .001
Error Low Mean Medium SD	.071	.017	< .001
Error High Mean Low SD	.158	.016	< .001
Error Middle High Mean Low SD	.201	.022	< .001
Error Middle Low Mean Low SD	.203	.030	< .001
Error Low Mean Low SD	.141	.016	< .001

Table 78. Squared Multiple Correlations SEM Model 14

Factor	Estimate
Low Mean Category	.078
Middle Low Mean Category	.223
Middle High Mean Category	.135
High Mean Category	.041
d' Low Mean Low SD	.135
d' Middle Low Mean Low SD	.426
d' Middle High Mean Low SD	.184
d' High Mean Low SD	.006
d' Low Mean Medium SD	.451
d' Middle Low Mean Medium SD	.411
d' Middle High Mean Medium SD	.593
d' High Mean Medium SD	.059
d' Low Mean High SD	.224
d' Middle Low Mean High SD	.190
d' Middle High Mean High SD	.393
d' High Mean High SD	.218

SEM Model 15: SEM Model Analysis of Cognitive Skills Interacting with Conscientiousness for Index *c* in Experiment 1

Table 79. Regression Weights for SEM Model 15

Path	Estimate	Standardized Estimate	Standard Error	*p*
Conscientiousness (Mean Centered) → High Mean Category	< .001	-.009	.001	.914
Conscientiousness (Mean Centered) → Middle High Mean Category	.002	.043	.003	.559
Conscientiousness (Mean Centered) → Middle Low Mean Category	.004	.050	.005	.495
Conscientiousness (Mean Centered) → Low Mean Category	.002	.052	.002	.484
Cognitive Skills (Mean Centered) → High Mean Category	.001	.131	< .001	.176
Cognitive Skills (Mean Centered) → Middle High Mean Category	.003	.218	.001	.007
Cognitive Skills (Mean Centered) → Middle Low Mean Category	.009	.348	.002	< .001
Cognitive Skills (Mean Centered) → Low Mean Category	.004	.394	.001	< .001
Cognitive Skills x Conscientiousness → High Mean Category	< .001	.104	< .001	.263
Cognitive Skills x Conscientiousness → Middle High Mean Category	< .001	-.013	< .001	.858
Cognitive Skills x Conscientiousness → Middle Low Mean Category	< .001	-.027	< .001	.714
Cognitive Skills x Conscientiousness → Low Mean Category	< .001	-.097	< .001	.195
High Mean Category → *c* High Mean Low SD	1.000	.274		
High Mean Category → *c* High Mean Medium SD	3.758	.701	1.252	.003
High Mean Category → *c* High Mean High SD	1.860	.398	.637	.003
Middle High Mean Category → *c* Middle High Mean Low SD	1.000	.525		
Middle High Mean Category → *c* Middle High Mean Medium SD	1.767	.885	.309	< .001
Middle High Mean Category → *c* Middle High Mean High SD	1.148	.587	.167	< .001
Middle Low Mean Category → *c* Middle Low Mean High SD	.762	.627	.089	< .001

Path	Estimate	Standardized Estimate	Standard Error	*p*
Middle Low Mean Category → *c* Middle Low Mean Medium SD	1.090	.829	.111	< .001
Middle Low Mean Category → *c* Middle Low Mean Low SD	1.000	.772		
Low Mean Category → *c* Low Mean Low SD	1.000	.511		
Low Mean Category → *c* Low Mean Medium SD	1.802	.707	.291	< .001
Low Mean Category → *c* Low Mean High SD	2.566	.784	.404	< .001

Table 80. Covariances SEM Model 15

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error High Mean ↔ Error Middle High Mean	.016	.672	.006	.004
Error High Mean ↔ Error Middle Low Mean	.017	.457	.006	.007
Error Middle High Mean ↔ Error Middle Low Mean	.076	.619	.017	< .001
Error Middle High Mean ↔ Error Low Mean	.021	.402	.006	< .001
Error Middle Low Mean ↔ Error Low Mean	.067	.813	.014	< .001
Error Middle Low Mean Low SD ↔ Error Low Mean Low SD	.018	.133	.012	.134
Error Middle Low Mean Medium SD ↔ Error Low Mean Medium SD	.006	.048	.016	.694
Error Middle High Mean Medium SD ↔ Error Middle Low Mean Medium SD	.023	.252	.016	.149
Error High Mean Medium SD ↔ Error Middle High Mean Low SD	.013	.087	.014	.345
Error High Mean Medium SD ↔ Error Middle Low Mean Low SD	-.066	-.519	.015	< .001
Error High Mean Medium SD ↔ Error Middle High Mean Medium SD	.007	.078	.022	.759
Error Low Mean High SD ↔ Error Middle Low Mean Low SD	.050	.313	.018	.004
Error Low Mean High SD ↔ Error Middle High Mean Medium SD	.032	.294	.017	.055
Error Middle Low Mean High SD ↔ Error Middle High Mean Low SD	.069	.333	.018	< .001
Error Middle Low Mean High SD ↔	.051	.276	.016	.002

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Low Mean High SD				
Error Middle High Mean High SD ↔ Error Low Mean High SD	.063	.335	.017	< .001
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.096	.474	.019	< .001
Error High Mean High SD ↔ Error Middle High Mean Low SD	.058	.342	.014	< .001
Error High Mean High SD ↔ Error Middle Low Mean Medium SD	-.032	-.258	.013	.015
Error High Mean High SD ↔ Error Middle Low Mean High SD	.028	.174	.014	.046
Error High Mean High SD ↔ Error Middle High Mean High SD	.066	.400	.014	< .001
Error Middle Low Mean High SD ↔ Error High Mean Medium SD	-.003	-.021	.015	.841
Error Middle Low Mean Medium SD ↔ Error Low Mean Low SD	-.024	-.199	.012	.048
Error Middle Low Mean High SD ↔ Error Middle High Mean Medium SD	.059	.498	.018	< .001
Error Middle High Mean High SD ↔ Error Middle High Mean Low SD	.050	.238	.020	.010
Error High Mean High SD ↔ Error Low Mean Low SD	-.019	-.155	.009	.028
Error High Mean High SD ↔ Error Middle .Low Mean Low SD	-.041	-.289	.014	.004
Error High Mean High SD ↔ Error Low Mean High SD	.015	.096	.013	.281
Error Low Mean High SD ↔ Error High Mean Medium SD	.022	.162	.016	.163

Table 81. Variances SEM Model 15

	Estimate	Standard Error	*p*
Conscientiousness (Mean Centered)	41.729	4.122	< .001
Cognitive Skills (Mean Centered)	323.634	31.966	< .001
Cognitive Skills x Conscientiousness	16953.833	1674.580	< .001
Error High Mean	.007	.004	.074
Error Middle High Mean	.079	.022	< .001
Error Middle Low Mean	.194	.033	< .001
Error Low Mean	.035	.010	< .001
Error High Mean High SD	.133	.015	< .001
Error Middle High Mean High SD	.207	.026	< .001
Error Middle Low Mean High SD	.199	.022	< .001
Error Low Mean High SD	.171	.030	< .001
Error High Mean Medium SD	.106	.032	< .001
Error Middle High Mean Medium SD	.072	.034	.038
Error Middle Low Mean Medium SD	.120	.025	< .001
Error Low Mean Medium SD	.135	.019	< .001
Error High Mean Low SD	.089	.009	< .001
Error Middle High Mean Low SD	.218	.025	< .001
Error Middle Low Mean Low SD	.150	.023	< .001
Error Low Mean Low SD	.118	.013	< .001

Table 82. Squared Multiple Correlations SEM Model 15

Factor	Estimate
Low Mean Category	.168
Middle Low Mean Category	.125
Middle High Mean Category	.049
High Mean Category	.028
c Low Mean Low SD	.261
c Middle Low Mean Low SD	.596
c Middle High Mean Low SD	.275
c High Mean Low SD	.075
c Low Mean Medium SD	.500
c Middle Low Mean Medium SD	.688
c Middle High Mean Medium SD	.783
c High Mean Medium SD	.491
c Low Mean High SD	.615
c Middle Low Mean High SD	.393
c Middle High Mean High SD	.345
c High Mean High SD	.159

SEM Model 16: Path Analysis of Cognitive Skills Interacting with Conscientiousness for Response Time in Experiment 1

Table 83. Regression Weights for SEM Model 16

Path	Estimate	Standardized Estimate	Standard Error	*p*
Conscientiousness (Mean Centered) → High Mean Category	1.442	.097	1.034	.163
Conscientiousness (Mean Centered) → Middle High Mean Category	.814	.042	1.356	.549
Conscientiousness (Mean Centered) → Middle Low Mean Category	.396	.019	1.413	.779
Conscientiousness (Mean Centered) → Low Mean Category	.447	.032	.982	.649
Cognitive Skills (Mean Centered) → High Mean Category	-.276	-.051	.371	.458
Cognitive Skills (Mean Centered) → Middle High Mean Category	.353	.050	.487	.468
Cognitive Skills (Mean Centered) → Middle Low Mean Category	.354	.048	.507	.486
Cognitive Skills (Mean Centered) → Low Mean Category	.222	.044	.353	.530
Cognitive Skills x Conscientiousness → Low Mean Category	-.053	-.076	.049	.274
Cognitive Skills x Conscientiousness → Middle Low Mean Category	-.081	-.081	.070	.247
Cognitive Skills x Conscientiousness → Middle High Mean Category	-.075	-.077	.067	.268
Cognitive Skills x Conscientiousness → High Mean Category	-.044	-.059	.051	.394

Table 84. Covariances SEM Model 16

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Error Middle High Mean ↔ Error Low Mean	11332.195	.995	1122.304	< .001
Error Middle Low Mean ↔ Error Low Mean	11643.797	.981	1161.225	< .001
Error Middle High Mean ↔ Error Middle Low Mean	15953.097	.973	1597.388	< .001
Error High Mean ↔ Error Low Mean	7129.984	.821	784.755	< .001
Error High Mean ↔ Error Middle Low Mean	10239.379	.820	1128.125	< .001
Error High Mean ↔ Error Middle High Mean	10189.355	.850	1099.047	< .001

Table 85. Variances SEM Model 16

	Estimate	Standard Error	*p*
Conscientiousness (Mean Centered)	41.729	4.122	< .001
Cognitive Skills (Mean Centered)	323.634	31.966	< .001
Cognitive Skills x Conscientiousness	16953.833	1674.580	< .001
Error High Mean	9140.455	902.830	< .001
Error Middle High Mean	15731.993	1553.896	< .001
Error Middle Low Mean	17072.633	1686.314	< .001
Error Low Mean	8250.212	814.898	< .001

Table 86. Squared Multiple Correlations SEM Model 16

Factor	Estimate
Low Mean Category	.009
Middle Low Mean Category	.009
Middle High Mean Category	.010
High Mean Category	.015

SEM Model 17: Analysis of Sensitivity in Experiment 2

Table 87. Regression Weights for SEM Model 17

Path	Estimate	Standardized Estimate	Standard Error	*p*
High Mean Category → *d'* High Mean Low SD	1.000	.262		
High Mean Category → *d'* High Mean Medium SD	1.617	.464	.800	.043
High Mean Category → *d'* High Mean High SD	1.538	.557	.841	.067
Middle High Mean Category → *d'* Middle High Mean High SD	1.716	.706	.277	< .001
Middle High Mean Category → *d'* Middle High Mean Medium SD	1.662	.708	.269	< .001
Middle High Mean Category → *d'* Middle High Mean Low SD	1.000	.533		
Middle Low Mean Category → *d'* Middle Low Mean Low SD	1.000	.550		
Middle Low Mean Category → *d'* Middle Low Mean Medium SD	1.288	.596	.220	< .001
Middle Low Mean Category → *d'* Middle Low Mean High SD	1.114	.656	.181	< .001
Low Mean Category → *d'* Low Mean Low SD	1.000	.150		
Low Mean Category → *d'* Low Mean Medium SD	2.825	.467	1.228	.021
Low Mean Category → *d'* Low Mean High SD	6.028	.944	3.226	.062

Table 88. Covariances SEM Model 17

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Middle High Mean Category ↔ Middle Low Mean Category	.070	.748	.016	< .001
High Mean Category ↔ Middle High Mean Category	.003	.104	.003	.370
Low Mean Category ↔ Middle Low Mean Category	.011	.531	.006	.080
Low Mean Category ↔ Middle High Mean Category	.005	.267	.003	.114
Error Low Mean Medium SD ↔ Error Low Mean Low SD	.038	.279	.010	< .001
Error Low Mean High SD ↔ Error Middle High Mean Low SD	-.031	-.547	.011	.004
Error High Mean Medium SD ↔ Error Low Mean Low SD	.035	.306	.009	< .001
Error High Mean High SD ↔ Error Middle High Mean Low SD	.021	.230	.008	.007

Table 89. Variances SEM Model 17

	Estimate	Standard Error	*p*
High Mean Category	.008	.007	.212
Middle High Mean Category	.074	.020	< .001
Middle Low Mean Category	.118	.032	< .001
Low Mean Category	.004	.004	.295
Error High Mean High SD	.044	.012	< .001
Error Middle High Mean High SD	.219	.033	< .001
Error Middle Low Mean High SD	.194	.026	< .001
Error Low Mean High SD	.017	.041	.672
Error High Mean Medium SD	.080	.015	< .001
Error Middle High Mean Medium SD	.203	.031	< .001
Error Middle Low Mean Medium SD	.355	.043	< .001
Error Low Mean Medium SD	.111	.014	< .001
Error High Mean Low SD	.115	.012	< .001
Error Middle High Mean Low SD	.186	.021	< .001
Error Middle Low Mean Low SD	.272	.031	< .001
Error Low Mean Low SD	.168	.016	< .001

Table 90. Squared Multiple Correlations SEM Model 17

Factor	Estimate
d' Low Mean Low SD	.023
d' Middle Low Mean Low SD	.302
d' Middle High Mean Low SD	.284
d' High Mean Low SD	.069
d' Low Mean Medium SD	.218
d' Middle Low Mean Medium SD	.355
d' Middle High Mean Medium SD	.501
d' High Mean Medium SD	.216
d' Low Mean High SD	.891
d' Middle Low Mean High SD	.430
d' Middle High Mean High SD	.498
d' High Mean High SD	.310

SEM Model 18: Analysis of Response Bias in Experiment 2

Table 91. Regression Weights for SEM Model 18

Path	Estimate	Standardized Estimate	Standard Error	*p*
High Mean Category → *c* High Mean Low SD	1.000	.416		
High Mean Category → *c* High Mean Medium SD	2.021	.725	.409	< .001
High Mean Category → *c* High Mean High SD	1.504	.609	.316	< .001
Middle High Mean Category → *c* Middle High Mean High SD	.877	.728	.082	< .001
Middle High Mean Category → *c* Middle High Mean Medium SD	1.074	.831	.088	< .001
Middle High Mean Category → *c* Middle High Mean Low SD	1.000	.780		
Middle Low Mean Category → *c* Middle Low Mean Low SD	1.000	.826		
Middle Low Mean Category → *c* Middle Low Mean Medium SD	.972	.819	.074	< .001
Middle Low Mean Category → *c* Middle Low Mean High SD	.837	.782	.071	< .001
Low Mean Category → *c* Low Mean Low SD	1.000	.511		
Low Mean Category → *c* Low Mean Medium SD	1.686	.648	.208	< .001
Low Mean Category → *c* Low Mean High SD	2.657	.929	.373	< .001

Table 92. Covariances SEM Model 18

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
Middle High Mean Category ↔ Middle Low Mean Category	.204	.788	.029	< .001
High Mean Category ↔ Middle High Mean Category	.061	.792	.014	< .001
Low Mean Category ↔ Middle Low Mean Category	.099	.807	.018	< .001
Low Mean Category ↔ Middle High Mean Category	.054	.520	.012	< .001
High Mean Category ↔ Middle Low Mean Category	.047	.516	.012	< .001
Low Mean Category ↔ High Mean Category	.010	.265	.004	.012
Error Middle High Mean High SD ↔ Error Middle Low Mean High SD	.065	.451	.013	< .001
Error Low Mean Medium SD ↔ Error Low Mean Low SD	.054	.328	.013	< .001
Error Middle Low Mean High SD ↔ Error Middle Low Mean Low SD	-.030	-.216	.013	.019
Error Middle Low Mean Medium SD ↔ Error Low Mean Medium SD	.042	.254	.013	.001
Error Low Mean High SD ↔ Error Middle High Mean Low SD	-.042	-.482	.013	< .001
Error Middle Low Mean Medium SD ↔ Error Middle High Mean Low SD	-.032	-.223	.012	.011
Error High Mean High SD ↔ Error Low Mean Low SD	-.025	-.212	.009	.004
Error Middle Low Mean Medium SD ↔ Error High Mean Low SD	-.025	-.185	.011	.019
Error Middle High Mean Medium SD ↔ Error High Mean Low SD	-.023	-.188	.010	.029
Error High Mean Medium SD ↔ Error Low Mean Low SD	-.022	-.191	.009	.016

Table 93. Variances SEM Model 18

	Estimate	Standard Error	*p*
High Mean Category	.027	.010	.007
Middle High Mean Category	.220	.034	< .001
Middle Low Mean Category	.306	.044	< .001
Low Mean Category	.049	.013	< .001
Error High Mean High SD	.103	.013	< .001
Error Middle High Mean High SD	.150	.017	< .001
Error Middle Low Mean High SD	.137	.017	< .001
Error Low Mean High SD	.055	.027	.042
Error High Mean Medium SD	.099	.016	< .001
Error Middle High Mean Medium SD	.114	.016	< .001
Error Middle Low Mean Medium SD	.142	.018	< .001
Error Low Mean Medium SD	.192	.021	< .001
Error High Mean Low SD	.129	.014	< .001
Error Middle High Mean Low SD	.141	.018	< .001
Error Middle Low Mean Low SD	.142	.020	< .001
Error Low Mean Low SD	.139	.014	< .001

Table 94. Squared Multiple Correlations SEM Model 18

Factor	Estimate
c Low Mean Low SD	.261
c Middle Low Mean Low SD	.683
c Middle High Mean Low SD	.609
c High Mean Low SD	.173
c Low Mean Medium SD	.420
c Middle Low Mean Medium SD	.670
c Middle High Mean Medium SD	.690
c High Mean Medium SD	.526
c Low Mean High SD	.863
c Middle Low Mean High SD	.611
c Middle High Mean High SD	.530
c High Mean High SD	.370

SEM Model 19: Analysis of Response Time in Experiment 2

Table 95. Regression Weights for SEM Model 19

Path	Estimate	Standardized Estimate	Standard Error	*p*
High SD → Median *RT* High Mean High SD	1.037	.833	.098	< .001
Medium SD → Median *RT* Middle High Mean Medium SD	1.525	.931	.150	< .001
Low SD → Median *RT* Low Mean Low SD	1.000	.643		
High SD → Median *RT* Middle High Mean High SD	1.394	.845	.131	< .001
Medium SD → Median *RT* High Mean Medium SD	1.131	.803	.114	< .001
Medium SD → Median *RT* Low Mean Medium SD	1.000	.617		
High SD → Median *RT* Low Mean High SD	1.000	.683		
Low SD → Median *RT* High Mean Low SD	1.108	.755	.115	< .001
Low SD → Median *RT* Middle High Mean Low SD	1.463	.766	.150	< .001
High SD → Median *RT* Middle Low Mean High SD	1.375	.825	.106	< .001
Medium SD → Median *RT* Middle Low Mean Medium SD	1.290	.743	.104	< .001
Low SD → Median *RT* Middle Low Mean Low SD	1.440	.792	.145	< .001

Table 96. Covariances SEM Model 19

Path	Covariance Estimate	Correlation Estimate	Standard Error	*p*
High SD ↔ Medium SD	280648.775	.522	55731.833	< .001
Low SD ↔ Medium SD	176181.886	.425	41872.831	< .001
Low SD ↔ High SD	179953.291	.414	41451.046	< .001
Error Middle Low Mean Medium SD ↔ Error Low Mean Medium SD	335603.499	.442	60736.178	< .001
Error Low Mean Medium SD ↔ Error Low Mean Low SD	221944.515	.352	44347.058	< .001
Error High Mean Medium SD ↔ Error High Mean Low SD	192321.892	.573	31565.984	< .001
Error High Mean High SD ↔ Error Middle High Mean Low SD	260372.849	.709	37923.611	< .001
Error Middle High Mean High SD ↔ Error Middle High Mean Low SD	311312.981	.661	48294.366	< .001
Error Middle Low Mean Medium SD ↔ Error Middle Low Mean Low SD	134192.884	.251	40770.445	< .001
Error Middle Low Mean High SD ↔ Error Low Mean High SD	170121.713	.300	52390.196	.001

Table 97. Variances SEM Model 19

	Estimate	Standard Error	*p*
High SD	563300.177	103561.385	< .001
Medium SD	512599.985	104320.804	< .001
Low SD	335786.593	65148.229	< .001
Error High Mean High SD	266293.200	38448.601	< .001
Error Middle High Mean High SD	437828.743	66472.640	< .001
Error Middle Low Mean High SD	497915.243	65908.910	< .001
Error Low Mean High SD	644763.907	68878.292	< .001
Error High Mean Medium SD	361662.354	47014.054	< .001
Error Middle High Mean Medium SD	183250.304	55720.289	.001
Error Middle Low Mean Medium SD	692590.594	77756.007	< .001
Error Low Mean Medium SD	834241.406	84959.467	< .001
Error High Mean Low SD	311118.394	39010.368	< .001
Error Middle High Mean Low SD	506475.710	63781.946	< .001
Error Middle Low Mean Low SD	413483.739	55608.086	< .001
Error Low Mean Low SD	475722.316	52206.680	< .001

Table 98. Squared Multiple Correlations SEM Model 19

Factor	Estimate
Median *RT* Low Mean Low SD	.414
Median *RT* Middle Low Mean Low SD	.627
Median *RT* Middle High Mean Low SD	.587
Median *RT* High Mean Low SD	.570
Median *RT* Low Mean Medium SD	.381
Median *RT* Middle Low Mean Medium SD	.552
Median *RT* Middle High Mean Medium SD	.867
Median *RT* High Mean Medium SD	.645
Median *RT* Low Mean High SD	.466
Median *RT* Middle Low Mean High SD	.681
Median *RT* Middle High Mean High SD	.714
Median *RT* High Mean High SD	.695

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