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Examining Evidence for a Taxonomy of Cognitive Biases

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14. ABSTRACT
This study tested Oreg and Bayazit's (2009) taxonomy of cognitive biases. Using a sample of 469 U.S. Army Soldiers and six biases that represented the proposed categorization, a variety of analyses were conducted to establish the validity of the taxonomy with the goal of advancing theory and the understanding of cognitive biases. However, little evidence was found in support of the taxonomy. Specifically, although verification and simplification biases were more strongly related to biases of the same category than to other categories, there was not a clear pattern for regulation biases. Moreover, individual differences (e.g., neuroticism) proposed by Oreg and Bayazit (2009) largely did not meaningfully predict heuristics-and-biases task performance. Overall, if research on cognitive bias is to be pragmatic and have real-world applications, cognitive bias as a construct needs to be better defined. In addition, measures of cognitive bias need to include both between- and within-subjects measures, and scoring methods should be revisited.

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VALIDITY OF HEURISTICS AND BIASES TAXONOMY

EXECUTIVE SUMMARY

Research Requirement:

A meaningful taxonomic approach is needed to advance cognitive heuristics and cognitive bias research. Oreg and Bayazit (2009) proposed a classification system that organizes biases according to the *shared underlying mechanisms* (i.e., individual differences) and *motivational end points* of biases. However, Oreg and Bayazit's (2009) propositions remain largely theoretical. Thus, the purpose of this study was to test the validity and utility of the taxonomy proposed by Oreg and Bayazit (2009). This study aimed (1) to test whether cognitive biases cluster into the three categories proposed and (2) to investigate whether biases share underlying mechanisms.

Procedure:

To assess the validity of the taxonomy and its propositions, several analyses were conducted to amass evidence. Specifically, we evaluated zero-order correlations, conducted an exploratory factor analysis, and evaluated the relationship between the underlying mechanisms (i.e., individual differences) and each heuristic and bias category. The final sample was composed of 469 active-duty U.S. Army officers and enlisted Soldiers stationed in the United States. Data were collected using paper-and-pencil questionnaires in a classroom setting.

Findings:

Negligible evidence was found to support relationships between individual differences and cognitive biases based on the taxonomy proposed by Oreg and Bayazit (2009). Empirical relationships between bias categories did not align with the proposed taxonomy, and the hypothesized relationships between individual differences and biases were mostly unsupported. A few encouraging findings did emerge. The pattern of correlations between biases within a category was more strongly positive than the pattern of correlations between biases from different categories. These results should not be taken to mean that the taxonomy is invalid; it is too early to determine that the taxonomic structure is not sufficient or not useful because our research only represents a single study.

Utilization and Dissemination of Findings:

The minimal findings of this study can serve as a presage to future cognitive bias research should efforts to improve measurement fail to take place. This paper can guide future areas of bias research, specifically with regards to enhanced measurement tools that need to be undertaken to advance the field. In addition, the findings point to understanding bias as a cognitive process rather than a trait-based individual difference. Future measurement should consider alternative methods to traditional psychometric assessments to evaluate the process in real time.

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Research on cognitive heuristics and biases has amassed strong evidence that human beings systematically use mental shortcuts that affect the quality of decision-making (Gilovich & Griffin, 2002). These biases have the potential to influence real-world outcomes. From an evolutionary or ecological perspective, cognitive heuristics can lead to positive outcomes because they help individuals make sense of the world by quickly analyzing complex information in order to make assumptions that help them adapt and survive (Gigerenzer & Brighton, 2009; Gigerenzer & Gaissmaier, 2010; Haselton et al., 2009). However, research demonstrates that when individuals over rely on cognitive heuristics, they can lead to decision biases, resulting in negative outcomes. For instance, venture capitalists may be inclined to refrain from, rather than engage in, investing in a startup company if they rely on the most recent piece of information they receive if that information is negative. If that information is negative (e.g., poor first impression of the founder), the venture capitalist may miss out on a lucrative investment as a result of the recency effect (Desjardins, 2017). In military settings, decisions are often made under conditions of uncertainty with limited information. Thus, it may be the case that utilizing heuristics, which can lead to cognitive bias, can have a negative impact on decision making. For example, insensitivity to sample size can lead to incorrect assumptions about whether a small or a large village is a greater threat (Williams, 2010).

As people come to recognize how these biases play a crucial role in all kinds of decisions from strategic leadership decisions to everyday health decisions, there is a growing need to understand why these biases occur and to develop programs to prevent bias. For instance, some organizations have turned their attention to understanding how to avoid cognitive bias, implementing human capital interventions to address the issue. The President's Task Force on 21st Century Policing, for example, recommended that police departments provide training on implicit biases to increase awareness of unconscious information processing as a means to enhance the practice of fair and impartial policing (U.S. Department of Justice [DOJ], 2015). Government agencies such as the U.S. Army and the Office of the Director of National Intelligence have also determined that understanding cognitive bias was central to improving the capabilities of their personnel (National Research Council [NRC], 2015). Such knowledge may also be incorporated more systematically into military training (Janser, 2008). However, in order to understand how to prevent bias, we must first understand *why* biases occur (Blacksmith et al., 2020c). In other words, we need to develop an understanding of the underlying mechanisms of cognitive bias to explain the covariance in cognitive bias task performance (Jackson et al., 2016).

One issue with advancing our understanding of why cognitive biases occur and what makes people susceptible to cognitive heuristics is that there is a proliferation of heuristics-and-biases tasks and theories. To date, an estimated 175 cognitive heuristics and biases have been specified in the scientific literature; thus, this vast and growing body of research is difficult to synthesize (Kasanoff, 2017; Oreg & Bayazit, 2009). It is worth noting that the number of cognitive heuristics is likely infinite because life events and individual difference factors can give rise to unique biases for each person. This view, referred to as the ecological perspective, explains that biases are acquired through learning and experience and emerge when environmental conditions do not match their own unique mental models (Gigerenzer, 2000; Korteling et al., 2018). For example, individuals who have high levels of body dissatisfaction are more prone to attention biases towards body image than those who have a lower dissatisfaction (e.g., Rodgers & Dubois, 2016). However, for the purposes and scope of this paper, we focused on biases that have been theorized to have an evolutionary or biological exposition or fall under the cognitive-psychological perspective (Evans, 2008; Haselton et al., 2009; Kahneman & Tversky, 1979; Korteling et al., 2018). For example, within cognitive and social psychology, biases studied are those that are attributed to limitations in human information processing (Evans, 2008; Kahneman & Klein, 2009). With regard to biases that have been studied under the evolutionary or cognitive-psychological perspective, a systematic and parsimonious investigation of underlying factors is currently unfeasible (but likely attainable) because the accrual of ostensible biases presents challenges to adequate synthesis and meta-analyses (Hough, 1992; Neal et al., 2012; Ployhart, 2006).

Preliminary research has evaluated relationships among heuristics and organized them into taxonomies, but the utility of extant taxonomies is limited (e.g., Ceschi et al., 2019; Stanovich et al., 2008). For example, Carter et al. (2007) developed a cognitive bias taxonomy, but the taxonomy offered limited generalizability because it focused exclusively on biases relevant to the field of supply chain management. Weaver and Stewart (2012) evaluated the factor structure of an uncomprehensive number of biases based on Hammond's (1996) conceptual categorization (i.e., correspondence and coherence), limiting the generalizability of the structure. Teovanović and colleagues (2015) took an exploratory approach and examined the relationships between several heuristics-and-biases tasks, but the collection of biases was not comprehensive. Although these initial efforts to classify cognitive heuristics have provided notable insights, they lack a unifying framework. Thus, a meaningful taxonomic and classification approach is needed to advance this stream of research (Meehl, 2004; Oreg & Bayazit, 2009).

In efforts to address the fragmented nature of current taxonomic work, Oreg and Bayazit (2009) inductively developed a classification system based on a comprehensive, systematic, literature review. Their classification system is organized according to the *shared underlying mechanisms* (i.e., individual differences) and *motivational end points* of biases. That is, biases that share motivational end points (e.g., achieving consistency) can be grouped together accordingly and, in turn, shared underlying mechanisms (e.g., individual difference predictors) can be identified more easily. Taxonomies based on shared underlying mechanisms have proven useful in other streams of psychological research such as clinical psychology (e.g., Lahey et al., 2017). Likewise, Oreg and Bayazit's (2009) taxonomy could be a useful starting point to advance cognitive bias research as it provides a strong explanatory foundation to understand why biases may occur. However, Oreg and Bayazit's (2009) propositions remain largely theoretical because few studies (cf. Augustine & Larsen, 2011) have attempted to empirically test them.

Thus, the purpose of this study was to test the validity and utility of the taxonomy proposed by Oreg and Bayazit (2009) as it was deemed to be the taxonomy that provides the closest approach to a unifying framework in the literature. There were two subgoals of this paper. First, we aimed to test whether cognitive biases cluster into the three categories proposed. That is, do cognitive heuristics used to achieve goals with the same purpose relate to one another? The second goal was to test whether the individual difference antecedents of each bias category were shared underlying mechanisms as hypothesized.

Current findings contribute to the science of cognitive bias in a number of ways. First, by examining proposed relationships of how biases are related to other biases and the role individual differences play in bias manifestation (a central part of the taxonomy), the nomological network around cognitive biases will be further developed. Second, building validity evidence for the taxonomy contributes to broad theories of cognitive biases and decision-making. Empirical tests of proposed models and taxonomies are a central part of the scientific method and necessary for theory testing (Cucina et al., 2014). Upon the return of results from empirical studies, scientists may alter a theory or model or discard it in favor of a new approach in order to realize the utility of the proposed theory or categorization scheme. Therefore, empirically testing proposed taxonomies is a necessary process in order to continue building and refining theories about the manifestations and processes that lead to cognitive bias.

Defining Heuristics and Biases

Cognitive *biases* are both referred to as an erroneous response (Gilovich & Griffin, 2002) and an accurate, adaptive response (Gigerenzer & Brighton, 2009) that manifests when people rely on cognitive heuristics in varying contexts (Kahneman, 2000). Cognitive *heuristics* are defined as unconscious mental shortcuts that people use to simplify the information computing process (Gilovich & Griffin, 2002). Through the use of cognitive heuristics (i.e., intuitive information processing), people can quickly process large amounts of information. Throughout the course of human history this has served as an adaptive response for making quick inferences about the world (Gigerenzer & Brighton, 2009). The theory of bounded rationality explains the necessity for reliance on heuristics for adaptive purposes. Specifically, according to the theory, human decision making power is limited because cognitive computing power is finite, there is a lack of comprehensive information, and decisions are time-bound (Simon, 1957, 1997). Thus, the use of cognitive heuristics, which leads to biased responses, can be thought of as a means of survival; humans cannot possibly gather and compute all accessible information in the environment and therefore need to rely on time-saving methods to interpret the world around them.

Dual process theory, which posits that people have two information processing systems that conflict with one another at times, offers an explanation for the theoretical underpinnings of cognitive heuristics and biases (De Neys, 2006; Epstein, 1994; Sloman, 1996). According to dual process theory, intuitive processing (also referred to as System 1) is unconscious and quick whereas analytical processing (also referred to as System 2) is effortful and slower in comparison (De Neys, 2006). Bias occurs when the intuitive processing system elicits a heuristic response and the analytical system fails to override the intuitive processing (Kahneman, 2000).

People's tendencies to rely on intuitive processing to process information influences the decisions they make in their lives in a variety of contexts (Blacksmith et al., 2020c). For example, in one study, participants were asked about the average price of German cars (Kahneman, 2000). Participants primed with the names of luxury brands (e.g., Mercedes, Audi) reported higher average prices than the participants primed with the names of mass-market cars (e.g., Volkswagen). That is, the names of the brands served as an anchor for the participants to make a judgment about the average price. Human susceptibility to biases, such as anchoring, can also be used as a strategic advantage. During World War II, as part of the Cyprus Defense Plan, the British used the anchoring heuristic to deceive German troops into thinking that there was a stronger defense than was actually present (Williams, 2010). The Germans believed the presence of the larger British forces despite their own analysis that showed that the larger number was unlikely.

The Role of Working Memory and Motivation in Susceptibility to Heuristics and Biases

People are more likely to rely on cognitive heuristics, and therefore be more susceptible to bias, when they have limited cognitive computing capacity, also referred to as working memory. Working memory is the ability to store, recall, manipulate, and reason with information while in a highly active cognitive state (Baddeley, 2012; Engle, 2002). Sufficient working memory is needed to engage in the analytical processing (i.e., System 2) that leads to an appropriate decision; people must recognize the need to override the initial, intuitive response (i.e., System 1) and then retrieve relevant information and reason with it during the decision-making process (Del Missier et al., 2012; Oppenheimer & Keslo, 2015). People with more working memory are likely to have the computing power necessary to override the intuitive response and engage in the analytical processing (Barrett et al., 2004; Quayle & Ball, 2000). In other words, people who have less working memory (low computing power) are more likely to engage in the use of cognitive heuristics because they do not have the capacity to override the intuitive response when making decisions.

Although out of scope for this paper, we would be remiss if we did not mention that executive function, another form of cognitive computing capacity, has been linked to performance on cognitive heuristics-and-biases tasks (e.g., Toplak et al., 2011). Executive function was not considered in this study because the relationship between executive function and working memory is exceedingly high, pointing to construct redundancy (McCabe et al., 2010). In addition, executive function is difficult to measure in studies that assess standardized assessments of individuals; the nature of executive function is such that it guides a person's behavior in novel, unstructured, and nonroutine situations (Banich, 2009). Addressing unique individual behavior and judgment in unstructured situations was not feasible nor relevant for the scope of this paper.

People are also more susceptible to cognitive heuristics when motivation to engage in analytical processing is low (Ployhart, 2006). Both state and trait motivation (e.g., Jiang & Kleitman, 2015; Kleitman et al., 2019) have been found to be related to cognitive bias and decision making. However, for the purposes of this research, we are focused on state motivation. People who are motivated to reach the "best" end state are more likely to put cognitive effort into reaching a sound decision and thus are more likely to use an analytical processing approach than the intuitive processing system (Kühberger, 2000; Wilson & Brekke, 1994). In other words, the degree to which the person is motivated to accomplish the decision-making task influences whether they make the effort to engage their working memory and override the heuristic to proceed to analytical processing. Thus, motivation may be a crucial component of understanding cognitive bias and thereby useful for categorizing and classifying a large number of biases.

Taxonomic Classification Based on Shared End Points and Underlying Mechanisms

The framework proposed by Oreg and Bayazit (2009) details classification of cognitive biases based on motivational end states. Specifically, engaging in cognitive bias helps a person attain an end goal. Oreg and Bayazit (2009) use motivational end goals to organize cognitive biases. By understanding why (i.e., their motivational end goal) someone may use cognitive heuristics, researchers can begin to develop hypotheses of shared underlying mechanisms of the resulting cognitive bias. In their taxonomy, because heuristics and their respective biases are categorized according to motivational end goals, Oreg and Bayazit (2009) argued that we should be able to gain a better, more parsimonious understanding of the shared underlying mechanisms through testing of explanatory hypotheses of how and why biases manifest. In sum, Oreg and Bayazit's (2009) taxonomy focuses on identifying individual differences that are predictive of motivational end goals in order to help explain how and why biases manifest. Existing knowledge about the relationship between individual differences and motivation was leveraged to inform the propositions underlying the taxonomy (e.g., Jiang & Kleitman, 2015). The three categories of the taxonomy, which they labeled verification, simplification, and regulation, are briefly described below to provide the reader with a basic understanding of how the taxonomy is organized. However, for a detailed description of the taxonomy, please refer to the original paper (see Oreg & Bayazit, 2009).

Verification Biases

Biases under the verification category are heuristics that aim to help people achieve consistency. According to self-verification theory, people are naturally inclined to maintain and confirm a consistent and coherent self-view (Oreg & Bayazit, 2009; Swann, 1983; Swann & Read, 1981; Swann et al., 1992). In order to maintain consistency between self-views and reality, people adjust or distort their perceptions of their own foresight, opinions, and judgments (Oreg & Bayazit, 2009; Pallier et al., 2002). Examples of verification biases studied in the scientific literature include hindsight bias and under/overconfidence (Oreg & Bayazit, 2009). Hindsight bias refers to a cognitive heuristic that leads individuals to believe an event is more likely or predictable after the event occurs in comparison to how likely they perceived the event prior to the event occurring (Roese & Vohs, 2012). Under/overconfident bias refers to the notion that individuals miscalibrate their judgments about their own capabilities (Alpert & Raiffa, 1982; Kahneman & Tversky, 1973).

Oreg and Bayazit (2009) proposed that one potential underlying mechanism related to verification biases is individual differences in core self-evaluations, which include dispositional traits such as self-esteem, neuroticism, locus of control, and generalized self-efficacy (Judge, 2009). For example, when confronted with environmental information that positions themselves in a positive light, individuals with lower self-esteem are more likely to distort that information by downplaying it in order to make it more consistent with their negative self-views, thereby meeting desires for achieving consistency (Hancock et al., 1996; Swann et al., 1992). Therefore, as Oreg and Bayazit (2009) suggested, a positive relationship between core self-evaluation traits and verification biases is likely.

Simplification Biases

Heuristics classified in the simplification category have a shared goal of comprehending reality. Specifically, simplification biases reflect people's failure to acquire and apply the appropriate or relevant information to accurately make sense of the world (Oreg & Bayazit, 2009). People fall prey to simplification biases when they apply cognitive distortions or inaccuracies to process information or analyze problems. Examples of heuristics that fall under the simplification category include belief bias (i.e., evaluating information based on the "believability" of the content) and base rate neglect (i.e., ignoring probability information; Evans et al., 1983; Teovanović et al., 2015; Tversky & Kahneman, 1983).

People are more likely to succumb to simplification biases when they have insufficient or incorrect information or lack the ability to adequately reason with all the relevant information (Oreg & Bayazit, 2009; Simon, 1957; Sternberg & Weil, 1980). As such, Oreg and Bayazit (2009) proposed that shared underlying mechanisms related to simplification biases include cognitive abilities such as general mental ability (GMA; i.e., the ability to process, store, and reason with information; Reeve & Bonaccio, 2011) and openness to experience (i.e., the inclination towards handling difficult or challenging material; Costa & McCrae, 1992; Goldberg, 1992, 1999; Johnson, 2014). Though not proposed by Oreg and Bayazit (2009), recent research points to flexible and fixed mindsets as another factor worth considering as an antecedent to simplification biases (Namaky et al., 2021).

People high in GMA are able to reason with information and are more likely to evaluate arguments in a logical manner rather than relying on belief arguments compared to those low in GMA (Oreg & Bayazit, 2009; Stanovich & West, 1998; Sternberg & Weil, 1980). Because people high on openness are likely to explore ideas and novel concepts, it is more likely that they would consider alternative options and make sure that they have the full picture while evaluating the problem. This extra contemplation would make them less likely to engage in simplification biases such as base rate neglect and belief bias. If Oreg and Bayazit's (2009) taxonomy were to be empirically supported, we would expect that people with higher openness to experience and higher GMA would engage in fewer simplification heuristics.

Regulation Biases

Regulation biases involve decisions and behaviors related to the human inclination to either approach pleasure or avoid pain (Oreg & Bayazit, 2009). Examples of regulation biases include framing effects (i.e., when people let how the information is presented, such as gain-framed or loss-framed, influence the decision) and the certainty effect (i.e., making decisions in uncertain situations leads people to take the least risky path; Kahneman & Tversky, 1979; Tversky & Kahneman, 1981, 1986). Oreg and Bayazit (2009) posit that approach temperaments (e.g., extraversion and neuroticism) influence people's susceptibility to regulate cognitive biases. Specifically, people high on approach temperaments focus on obtaining positive outcomes and therefore are sensitive to the presence or absence of gains (Isen & Patrick, 1983). Conversely, people with avoidance temperaments are sensitive to the presence or absence of losses (Mann et al., 2004; Sherman et al., 2006; Vazquez, 1987). Oreg and Bayazit (2009) consider extraversion and neuroticism as approach and avoidance temperaments, respectively. People high on extraversion seek (i.e., approach) excitement and experience positive emotions while people high on neuroticism attempt to circumvent (i.e., avoid) negative outcomes because they are more sensitive (Costa & McCrae, 1992; Elliot & Thrash, 2002; Watson & Clark, 1992). Empirical support for Oreg and Bayazit's (2009) taxonomy would manifest as people high in approach temperaments seeking risk in gain-framed situations and showing risk aversion in loss-framed scenarios. People high in avoidance temperaments should be risk averse when situations are gain-framed and risk seeking when situations are loss-framed.

Expected Support for Taxonomy

Validity is not a dichotomous existence or absence concept. Rather, validity is a judgment of how accumulated evidence supports claims that follow from theories and hypotheses. Building the strength of validity judgments requires that evidence is developed over time using a variety of measures and methods. The more supporting evidence, the stronger the claim of validity. Thus, in order to provide support for the validity of Oreg and Bayazit's (2009) taxonomy of cognitive biases, we conducted several analyses that could offer supporting evidence.

To assess the validity of the claim that biases can be organized into types, we considered the relationships between bias categories. First, we evaluated zero-order correlations (Evidence A1). For evidence in support of the taxonomy, we expected stronger positive correlations of heuristics-and-biases tasks *within* bias categories than relationships *between* categories. Second, an exploratory factor analysis[1] was conducted to examine if the factor structure of the heuristics-and-biases tasks proposed by Oreg and Bayazit (2009) would be distinguishable (Evidence A2). Specifically, we expected to see three distinct factors representing the three categories of bias. Third, we evaluated the relationship between the underlying mechanisms (i.e., individual differences) and each category. Specifically, neuroticism was expected to be positively related to the manifestation of verification biases (i.e., hindsight bias, under/overconfidence; Evidence B). We expected that having higher openness to experience (Evidence C) and GMA (Evidence D) would result in fewer simplification biases (i.e., belief bias, base rate neglect)[2]. We also expected that extraversion would be positively related to manifestation of framing effects (gain) and the certainty effect (Evidence E1), and that extraversion would be negatively related to framing effects (loss; Evidence E2). Finally, we expected that neuroticism would be positively related to the certainty effect and framing effects (loss; Evidence F1) and that neuroticism would be negatively related to framing effects (gain; Evidence F2).

In addition to providing evidence that would support the validity of the taxonomy, this study contributes to the broader literature on the nomological network of cognitive biases by examining their relationships with working memory and state motivation. Therefore, it was expected that working memory would be negatively related to the manifestation of all cognitive biases (Evidence G), as past research has shown that reduced cognitive capacity was related to

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[1] The structure of the biases is unknown because preliminary empirical evidence does not yet exist. Thus, we conducted an exploratory factor analysis, rather than confirmatory analysis, and examined eigenvalues (using a parallel analysis) and factor loadings.

[2] Because simplification biases were scored such that higher scores meant less bias, support for the taxonomy would be in the form of a positive relationship between openness to experience and GMA with simplification biases.

the likelihood of engaging in cognitive bias (e.g., Booth et al., 2016). In addition, state motivation was expected to interact (Evidence H) with individual difference predictors. This interaction is critical to consider because an individual may possess the individual differences that predict avoidance of the bias, but if they are not motivated to put in effort to analytically process the information, they may provide a biased response regardless. In a case where an individual with capability lacks motivation, it would be misleading to conclude that the individual differences were not related to the biases if an insignificant or negligible relationship between the individual differences and biases emerges in the results. Because the bias responses, in this example, were a result of not engaging in analytical processing (i.e., effort), it is not possible to infer whether the individual differences had predictive power. Appendix A describes each piece of evidence that would support the taxonomy.

Method

Sample and Procedure

The sample was composed of 603 active-duty U.S. Army officers and enlisted Soldiers stationed in the United States. Based on the analysis we planned to conduct, a power analysis revealed that a sample size of either 395 or 485 was needed to detect small effects. Based on a quality control question, failure to follow directions, and incompletion of the survey, some cases (n = 134) were screened out leaving a final sample size of 469.[3] Participants who reported demographic information were mostly male (77%) and Caucasian (63%). Participants had a range of age and educational experience. Specifically, participants ranged in age from 20 to 52 years with an average age of 30.77[4] years (SD = 6.10). For participants who provided education information, about half reported obtaining a bachelor's degree (48.9%). Other participants had a high school education (20%), an associate's degree (16.1%), and a master's degree (9.1%). Data were collected using paper-and-pencil questionnaires in a classroom setting.

Measures

Six biases that were representative of the three categories of Oreg and Bayazit's (2009) taxonomy of cognitive biases were chosen. In addition, GMA, working memory, personality, and state motivation (i.e., test-taking motivation) were measured. Appendix B provides example questions from the heuristics-and-biases tasks. Heuristics and biases were chosen to the extent that there were existing measures of the bias in the literature that were used in within-subjects designs or there were enough unique tasks to combine and create a scale score.

Verification Biases

Hindsight bias (composite reliability [*CR*] = .41) was measured using 10 items adapted from Teovanović and colleagues (2015). Questions were answered in two phases. First,

[3] Some participants received black-and-white materials instead of color materials, which prevented the hindsight bias measure from being scored correctly. Thus, an additional 101 participants were screened out for analyses involving hindsight bias.

[4] Not all participants reported demographic information; thus here, n = 429. Two outlier cases reporting that age was 1 were excluded from this analysis.

participants were given five words and asked which word most closely matched another word in capital letters. Participants rated their confidence in their response. Later in the survey, participants were presented with the same items with correct answers marked and asked to recall how confident they were in their initial choice. Responses were coded as "biased" if (a) participant responses were correct and participants marked an increase in confidence on recall compared to what they originally marked prior to knowing the results or (b) participant responses were incorrect and participants exhibited a decrease in confidence on recall compared to what they originally marked prior to knowing the results. All other responses were coded as "not biased." The total score represented the degree of hindsight bias. *Under/overconfidence* (*CR* = .54) was measured with 12 items (adapted from Bruine de Bruin et al., 2007) that asked respondents to answer a question that had a single correct answer. Scores were calculated based on the ratio between accuracy and judgment of confidence; high scores indicated overconfidence and low scores indicated underconfidence. In other words, the miscalibration between one's actual capabilities and the judgment of their capabilities represented the bias.

Simplification Biases

Belief bias (*CR* = .80) was measured using eight syllogistic reasoning items (Marcus-Blank et al., 2015) that measured a person's capacity to evaluate deductive arguments on the basis of logical validity rather than on the basis of believability (Evans et al., 1983; Markovits & Nantel, 1989). Participants were instructed to respond by indicating whether or not the conclusion of the item followed logical premises. *Base rate neglect* (*CR* = .82) was measured by instructing participants to choose which option was more probable after reading each of five scenarios (Marcus-Blank et al., 2015). Both simplification biases were scored on a continuum such that more correct answers (less bias) equaled higher scores.

Regulation Biases

Framing bias (Gain Frame *CR* = .54, Loss Frame *CR* = .71) was measured using a subtest from the Adult-Decision Making Competence test (A-DMC) developed by Bruine de Bruin and colleagues (2007). Seven pairs of items each presented a scenario framed as a gain and as a loss with two options. Participants rated which option they would choose from 1 (*Definitely would choose A*) to 6 (*Definitely would choose B*). Option A always presented a sure option and Option B always presented a risky or unsure option. The degree of bias was the mean score for the gain-framed or the loss-framed scenarios. The *certainty effect* (*CR* = .23) was measured with three pairs of scenarios with each scenario posing two different gamble options from which the respondent had to choose (Allais, 1953; Marcus-Blank et al., 2015). These items challenge the idea that adding a constant probability to each outcome will not change results proposed by expected utility theory. Each scenario of the pair proposes options for the same gamble (11% chance of winning $1 million vs. 10% chance of winning $5 million, 1% chance of nothing), but each scenario adds a different constant to both options. The effect manifested if the respondent did not choose the same option in both scenarios (i.e., the language about certainty affected choices). The outcomes of bias for the three pairs were summed to create the score.

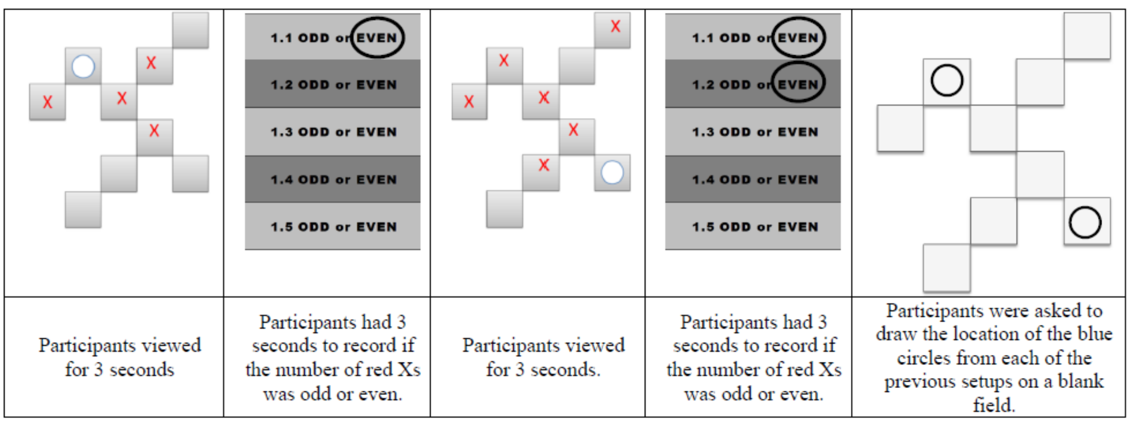
Individual Differences

GMA. GMA (*CR* = .79) was measured using the International Cognitive Ability Resource (ICAR) Sample Test. The sample test is comprised of 16 items (Condon & Revelle, 2014; http://icar-project.org/) and included item types of Letter and Number Series, Matrix Reasoning, Verbal Reasoning, and Three-Dimensional Rotation.

Working Memory. Working memory (*CR* = .66) was measured using three tasks that varied in content and in method: (a) backwards digit span task; (b) backward letter span task (Oberauer et al., 2000); and (c) a visual-spatial span task (Ackerman et al., 2002; Hambrick & Oswald, 2005). Working memory experts were consulted to develop a sound approach to assessing working memory in a group setting, recommending that multiple tasks that spanned various cognitive domains (e.g., spatial, numerical, and verbal) be included. Participants completed two practice items for each of the three tasks before beginning the actual task. The backwards digit and letter span tasks had 15 items each, and the visual-spatial span task had 12 items. See Figure 1 for an illustration of the visual-spatial span task. Scores from all three components were summed to compute an overall working memory score.

Figure 1

Example Spatial Working Memory Item



Note. The order that participants saw the stages is presented from left to right.

Test-Taking Motivation. Test-taking motivation (*CR* = .91) was measured using a modified 10-item measure (Arvey et al., 1990). Responses were on a 5-point Likert scale from 1 (*Strongly Disagree*) to 5 (*Strongly Agree*). An example item was, "I pushed myself to work hard on section 2." Two items were reverse-coded.

Personality. The personality traits of neuroticism, openness to experience, and extraversion (*CR*s = .78, .68, .75, respectively) were measured using items from a Big 5 inventory on the International Personality Item Pool (Goldberg, 1992, 1999; Goldberg et al., 2006) using a 5-point scale from (1) *Very Inaccurate* to (5) *Very Accurate*.

Control Variables

Research has demonstrated that older people with more education tend to perform better on some heuristics-and-biases tasks than younger, less educated people (Bruine de Bruin et al., 2007; Toplak et al., 2017; Welsh & Begg, 2017). Heuristics-and-biases tasks used in the literature typically require that a person have a certain level of knowledge and vocabulary to respond. As people age, they are able to gain more education and have more experiences through which they can gain knowledge. However, as people age, levels of cognitive capacity, such as memory and speed, begin to decline slowly and naturally (Deary et al., 2009; Salthouse, 2019). Thus, to understand the unique effects of the individual differences, we controlled for age and educational attainment in regression analyses.

Analysis

Three types of analyses were used to provide support for the taxonomy: patterns of zero-order correlations, exploratory factor analysis (EFA), and moderated hierarchical multiple regression. To address our first subgoal and evaluate the relationship between cognitive biases, we evaluated correlations and conducted an EFA. To address our second subgoal, we conducted moderated hierarchical multiple regression with listwise deletion. Generally, missing data for any item was less than 5%.

We conducted several different analyses because we aimed to evaluate the relationships between the constructs from a variety of perspectives. For instance, factor analysis will provide evidence about the internal structure of cognitive bias categories. However, we postulate that factor analysis may not be an ideal approach to analysis for our purposes because it assumes that observed measures are a combination of an underlying *exogenous* factor (Kim & Mueller, 1978). Factor analyses conducted will thus be of an exploratory nature. Scores on cognitive heuristics-and-biases tasks, however, are potentially observed (measured) *endogenous* variables that theoretically arise from the interaction between numerous antecedents (e.g., individual differences) and situational factors (Oreg & Bayazit, 2009). Previous research has found little evidence for strong latent factors of cognitive bias (Jackson et al., 2016). Yet, the field is still mixed on whether there is an underlying trait that explains performance on heuristics and biases tasks and therefore we conducted an EFA to explore and mitigate any confusion (e.g., Stanovich & West, 2008). We would expect that if cognitive heuristics and biases are related latent factors, then clusters representing Oreg and Bayazit's categories will emerge. Alternatively, if the tasks best represent observed measures there will likely be an absence of common factors representing the underlying processes (Tabachnick & Fidell, 2013). Indeed, research in this domain is still novel and scant, therefore we aim to examine whether or not latent factors emerge from cognitive biases tasks. Thus, we conducted exploratory factor analysis using scale scores for cognitive heuristics-and-biases tasks.

To further evaluate the relationships between biases from another perspective we followed similar papers (e.g., Lahey et al., 2017) and assessed *patterned relationships* between biases and hypothesized antecedent variables (i.e., individual differences) using bivariate correlation coefficients. Even if the EFA demonstrates that there is no shared variance or latent factor structure, it is possible that relationships exist between specific pairs of biases. The focus here was on the bias categories and the relationships between pairs of measures within categories.

Regression analyses were conducted using raw variables. A continuous score was computed for all bias measures. Age and education control variables were entered in Step 1 followed by working memory and motivation in Step 2. Individual difference variables proposed by the taxonomy were entered in Step 3, and interaction terms between individual difference variables and motivation were entered in Step 4.

Results

Descriptive statistics for all study variables are presented in Table 1; correlations between study variables can be found in Table 2.[5] R version 3.5.1 and the lavaan package (v. 0.6-5) were used to test measurement models and obtain composite reliability values. Reflective measurement models of predictor variables were evaluated using confirmatory factor analysis. For the measurement model specification, subscales (of the narrow facets) for each predictor were used as indicators of the respective latent variable to maintain reliability and strong statistical power. For example, the average scores from the six neuroticism subscales (anxiety, anger, depression, self-consciousness, immoderation, and vulnerability) were modeled as six indicators of the latent variable neuroticism instead of all 30 items as indicators to lessen the risk for nonconvergence or an improper solution (Brown, 2015). Using MacCullum et al.'s (1996) and Hu and Bentler's (1999) recommended cut-off values and their recommendation to look across several fit indices, all models exhibited acceptable fit when taking into account all fit indices and model complexity. In summary, tested models had coefficients as follows: all CFIs $\geq$ .78, all RMSEAs $\leq$ .16, and all SRMRs $\leq$ .09. Exploratory factor analysis was used to examine the factor structure of the bias scale scores.

Moderated multiple hierarchical regression using raw variable scores was used to examine how well individual differences and their interactions (Aguinis & Gottfredson, 2010) predicted heuristics-and-biases task performance using SPSS 25. In the current analyses we focused on understanding main effects *and* interactions (Aguinis & Gottfredson, 2010). Therefore, variable scores were not centered as centering is only to aid interpretation and does not change statistical significance. Assumptions of multiple regression including normality, linearity, homoscedasticity, and multicollinearity were tested and met (Aguinis, 2004; Aguinis & Gottfredson, 2010). Based on a power analysis, there was good evidence that small effects would be found if they existed. For each piece of evidence supported by a hierarchical regression, the required sample sizes for each analysis (α = .05, β = .80, effect size = .02) was either 395 or 485. See Appendix A for a summary of proposed support and results.

Evidence from Zero-Order Correlations

Evidence A1

Zero-order correlations were used to examine the relationships between and within bias

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[5] Portions of these data were accepted for presentation at the 2020 Society for Industrial and Organizational Annual Conference in Austin, Texas (Blacksmith et al., 2020a, 2020b). See Appendix C.

categories using the total scale scores. (The within category correlations are in bold in Table 2.) There was a moderate positive correlation between hindsight bias and under/overconfidence (r = .37, p < .001; verification biases) and between belief bias and base rate neglect (r = .46, p < .001; simplification biases). However, the relationships between framing (gain) and the certainty effect, r = -.02, p = .69, and framing (loss) and the certainty effect, r = -.07, p = .17, were negligible.

Verification biases had a small negative average correlation with simplification biases (r = -.23) and a negligible relationship with regulation biases (r = .07). On average, simplification and regulation biases also had a trivial relationship (r = -.02).

Hindsight bias and under/overconfidence had a stronger positive relationship with each other than hindsight bias and under/overconfidence did with all simplification and regulation biases, all zs ≥ 2.53, ps < .05. Likewise, the relationship between belief bias and base rate neglect was more strongly positive than any of the relationships between belief bias and base rate neglect and the other biases, all zs ≥ 4.51, ps < .05. In contrast, for all but one comparison, the relationship that the regulation biases (gain and loss framing and the certainty effect) had with each other was not different from the relationships that regulation biases had with verification or simplification biases, all zs ≤ |1.59|, ps > .05. Not providing support for the taxonomy, the relationship between framing (loss) and the certainty effect was smaller than the relationship between framing (loss) and under/overconfidence, z = -2.74, p = .01. Together, these results provide moderate partial support for Evidence A1.

Evidence from Exploratory Factor Analysis

Evidence A2

An exploratory factor analysis (EFA), using principal axis factoring with oblimin rotation, was conducted to investigate the factor structure of the seven biases (i.e., total scale scores for each bias). Should Oreg and Bayazit's (2009) taxonomy hold up, we expected that the biases would group together by the three bias categories. Based on the taxonomy, one would expect a parsimonious structure of three factors to emerge (i.e., factors for verification, simplification, and regulation biases). In order to determine factor retention, we conducted a parallel analysis to examine which factors had greater than chance likelihood to emerge (Hayton et al., 2004). Parallel analysis overcomes limitations of traditional methods (e.g., eigenvalue, scree plot) of determining which factors to retain (Glorfeld, 1995). We followed recommendations from experts (e.g., Bandalos & Finney, 2010; Costello & Osborne, 2005; Kline, 1994) to comprehensively interpret all relevant parameter values. Thus, parameter values including factor correlations, loadings (i.e., structure coefficients and pattern coefficients), and communalities were used to evaluate fit. More specifically, we examined which biases correlated highly with the latent factor and how much variance was explained by the factors (Gorsuch, 1983). A cut-off of $\lambda = |.30|$ (i.e., 10% variance) was used to judge the strength of the factor loading (Bandalos & Finney, 2010; Costello & Osborne, 2005; Kline, 1994).

Table 1

Descriptive Statistics

Variable	*n*	Min	Max	Mean	*SD*	Var	Skew	Kurtosis	Cronbach's Alpha	Composite Reliability
Verification Biases										
Hindsight	297	0.00	10.00	3.64	1.76	3.08	.51	.31	.45	.41
Under/overconfidence	468	-156.67	-23.83	-76.18	12.71	161.50	.14	3.70	.56	.54
Simplification Biases										
Belief Bias	467	0.00	8.00	3.71	2.54	6.45	.29	-1.11	.81	.80
Base Rate	463	0.00	7.00	4.04	2.33	5.43	-.26	-1.32	.80	.82
Regulation Biases										
Framing (Gain)	468	1.00	5.43	2.72	.86	.74	.27	.004	.51	.54
Framing (Loss)	457	1.00	6.00	3.32	1.04	1.09	-.09	-.38	.70	.71
Certainty Effect	458	0.00	3.00	1.32	.87	.76	.10	-.72	.06	.23
Individual Differences										
GMA	469	0.00	16.00	7.80	3.67	13.43	.13	-.73	.79	.79
Working Memory	392	4.00	42.00	24.09	6.53	42.70	-.08	-.13	.83	.66
Test-Taking Motivation	464	1.00	5.00	3.91	.69	.48	-.84	1.68	.92	.91
Neuroticism	468	1.07	4.10	2.23	.52	.27	.31	-.06	.89	.78
Openness	468	2.00	4.50	3.39	.46	.21	-.21	.07	.83	.68
Extraversion	468	1.87	4.87	3.55	.47	.22	-.18	.23	.88	.75

Note. n = sample size. *SD* = standard deviation. Var = variance. Skew = skewness. Min = minimum score. Max = maximum score. The assumptions of tau equivalency were not met for the data. Therefore, composite reliability is presented. However, because of the widespread use of alpha (i.e., Cronbach's alpha) as a reliability coefficient, those values are presented as well for comparison (Cho, 2016).

Table 2

Correlations Between Study Variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1. Hindsight Bias (V)	(.41)														
2. Under/overconfidence (V)	**.37***	(.54)													
3. Belief Bias (S)	-.22*	-.29*	(.80)												
4. Base Rate Neglect (S)	-.07	-.32*	**.46***	(.82)											
5. Framing - Gain (R)	.07	.09	.02	.02	(.54)										
6. Framing - Loss (R)	.05	.16*	-.12*	-.08	**.54***	(.71)									
7. Certainty Effect (R)	.03	.05	.08	.01	**-.02**	**-.07**	(.23)								
8. GMA	-.24*	-.41*	.55*	.48*	-.02	-.13*	.03	(.79)							
9. Working Memory	-.02	-.17*	.26*	.27*	.01	-.02	-.04	.42*	(.66)						
10. T-T Motivation	-.01	-.22*	.21*	.21*	.02	-.01	.01	.36*	.26*	(.91)					
11. Neuroticism	.03	.10*	-.07	-.11*	.04	.06	-.03	-.04	-.07	-.07	(.78)				
12. Openness	-.20*	-.18	.10*	.05	.01	.01	.02	.17*	.06	.16*	-.16*	(.68)			
13. Extraversion	.07	.03	-.03	-.04	.01	.00	.00	-.01	.06	.14*	-.45*	.28*	(.75)		
14. Age	.04	.04	-.25*	-.13*	.01	.11*	-.08	-.21*	-.14*	-.07	.03	-.05	-.17*	-	
15. Gender	-.04	.16*	-.14*	-.15*	.05	.13*	-.01	-.14*	-.11*	-.08	.05	-.02	-.04	.00	-
16. Education	.05	-.13*	.19*	.24*	-.01	-.04	.01	.24*	.11*	.14*	-.09	.14*	.01	-.11	.03

Note. N = 252 – 469. * p < .05. V = verification bias. S = simplification bias. R = regulation bias. Male = 1. Female = 2. T-T = Test-Taking. Composite reliability is on the diagonal in parentheses. Values in bold represent within-category correlation coefficients.

The data showed that three factors were present, the same number a parallel analysis suggested may occur by chance. For Factor 1, verification biases had weak positive loadings, simplification biases had moderate to strong negative loadings, and regulation biases had weak positive and negative loadings. For Factor 2, verification biases, simplification biases, and the certainty scale (a regulation bias) had negligible loadings; the two framing biases had strong positive loadings. For Factor 3, verification biases had moderate positive loadings, simplification biases and framing scales had negligible loadings, and the certainty scale had a weak positive loading. The factors had weak relationships (r_{12} = .09, p = .11; r_{13} = .13, p = .03; r_{23} = .13, p = .03). See Table 3 for a summary of results from the bias scale score EFA. Taken together, these results provide partial support for the separation of verification, simplification, and regulation bias categories (Evidence A2).

Evidence From Moderated Multiple Regression

We observed that education and age had small, significant relationships with some of the biases. Specifically, education had a small negative relationship with under/overconfidence (r = -.13, p = .008) and small positive relationships with belief bias (r = .19, p < .001) and base rate neglect (r = .24, p < .001). Age had small negative relationships with belief bias (r = -.25, p < .001) and base rate neglect (r = -.13, p = .007), and a small positive relationship with framing (loss; r = .11, p = .02). Thus, two variables (age and education) were included as control variables[6] by entering them into Step 1 of the regressions.

Table 3

Exploratory Factor Analysis Loadings for Heuristics-and-Biases Tasks Scale Scores

Heuristic-and-Bias Scale	**Extraction Communality Estimates**	**Factor 1** (λ = 1.96)	**Factor 2** (λ = 1.49)	**Factor 3** (λ = 1.09)
Hindsight Bias (V)	.27	.16	.01	.47
Under/Overconfidence (V)	.54	.28	.04	.64
Belief Bias (S)	.60	-.76	.02	-.07
Base Rate Neglect (S)	.31	-.55	-.03	-.03
Framing Effects (Gain) (R)	.57	-.07	.75	.03
Framing Effects (Loss) (R)	.62	.06	.79	-.04
Certainty Effect (R)	.04	-.11	.00	.17
% Variance Explained		28.06	21.27	15.63

Note. V = verification bias. S = simplification bias. R = regulation bias. Total estimated variance explained = 64.96%.

[6] Results including control variables were generally similar to results that did not include the control variables. Only two direct effects became significant when the control variables were not included: motivation became a significant predictor for under/overconfidence (negative coefficient) and belief bias (positive coefficient). Thus, because of the limited difference in results, the results with controls are presented because of the theoretical relevance of age and education to heuristics-and-biases task performance.

Following entry of control variables in Step 1, working memory and motivation were entered in Step 2 of the regressions. Working memory was entered in Step 2 because theory repeatedly suggests that biases emerge because of a lack of working memory (e.g., Evans & Stanovich, 2013). Thus, we expected the relationship to exist and wanted to determine whether individual differences added incremental predictive value. Motivation was added in Step 2 because in order to "override" intuitive processing (i.e., System 1), people must put in effort, which requires them to be motivated to do well. Had we not included motivation we would not be able to discern between individuals who had the ability to override but lacked the motivation, and the individuals who had motivation but lacked abilities. In other words, individuals with higher ability will only move on to analytical processing (i.e., System 2) if they are motivated to do so (Evans & Stanovich, 2013). Including motivation in Step 2 allowed for more confidence in the unique contribution of the individual differences proposed by the taxonomy. Individual differences predicted to be relevant for each bias category were entered into Step 3, and interaction terms between individual differences and motivation were entered in Step 4.

Evidence B

To test for the presence of the shared underlying mechanism of neuroticism in predicting verification biases, it was entered into the regression equation in Step 3. However, neuroticism was not a meaningful predictor for hindsight bias ($\beta = .03$, $p = .72$) or under/overconfidence ($\beta = .07$, $p = .19$). Although the pattern of results is in the expected direction, these results provide weak support for Evidence B.

Evidence C and D

To test for the presence of shared underlying mechanisms of openness to experience and GMA as predictors of simplification biases, those variables were entered into the regression equation in Step 3. Openness to experience was a negligible predictor for belief bias ($\beta = -.03$, $p = .47$) and base rate neglect ($\beta = -.07$, $p = .14$). Accordingly, the results for openness to experience do not provide support for Evidence C. In contrast to openness to experience, GMA positively predicted belief bias ($\beta = .49$, $p < .001$) and base rate neglect ($\beta = .41$, $p < .001$) when entered in a hierarchical regression. Because higher scores on the simplification bias measures represent less bias, the results for GMA provide support for Evidence D.

Evidence E and F

To test for the presence of shared underlying mechanisms of extraversion and neuroticism as predictors of regulation biases, those variables were entered in Step 3 of the regression equation. Extraversion was a negligible predictor of framing (gain; $\beta = .03$, $p = .62$), framing (loss; $\beta = .05$, $p = .38$), and the certainty effect ($\beta = -.02$, $p = .76$). Because these effects are trivial in size and some trended in opposite the expected direction, these results provide very weak to no support for Evidence E. Neuroticism was a trivial predictor in opposite the predicted direction for framing (gain; $\beta = .05$, $p = .38$) and the certainty effect ($\beta = -.07$, $p = .29$). However, neuroticism was a meaningful predictor of framing (loss; $\beta = .14$, $p = .03$), providing partial support for Evidence F.

Evidence G

To test working memory as a predictor of all of the heuristics-and-biases tasks, it was entered in Step 2 of all regression equations. Working memory was a significant positive predictor of belief bias (β = .21, $p < .001$) and base rate neglect (β = .24, $p < .001$), and a significant negative predictor of under/overconfidence (β = -.18, $p = .001$). However, working memory was not a meaningful predictor for hindsight bias (β = -.05, $p = .49$), framing (gain; β = -.03, $p = .61$), framing (loss; β = -.02, $p = .72$) or the certainty effect (β = -.04, $p = .53$). Overall, these results provide weak partial support for Evidence G.

Evidence H

The synergistic effects of motivation and individual differences on all heuristics-and-biases tasks were also tested by entering test-taking motivation and the relevant individual difference(s) as independent effects in Step 2 and Step 3, respectively, and the cross-product term(s) in Step 4. No meaningful interaction terms were present: hindsight bias, β = -.22, $p = .65$, for neuroticism interaction; under/overconfidence, β = -.53, $p = .16$, for neuroticism interaction; belief bias, βs = -.79, .53, *p*s = .07, .09, for openness and GMA interactions, respectively; base rate neglect, βs = -.84, .09, *p*s = .07, .77, for openness and GMA interactions, respectively; framing (gain), βs = -.32, -.88, *p*s = .59, .05, for extraversion and neuroticism interactions, respectively; framing (loss), βs = .59, .15, *p*s = .33, .74, for extraversion and neuroticism interactions, respectively; and the certainty effect, βs = -.03, .07, *p*s = .97, .87, for extraversion and neuroticism interactions, respectively. Thus, these results do not provide support for Evidence H. Tables in Appendix D show results from the regression analyses.

Discussion

Little is known about *how* person factors affect the manifestation of cognitive biases. Most existing research has treated unexplained variance on measures of cognitive bias as a measurement artifact or ignored it, leaving a gap in our understanding of why people are susceptible to cognitive biases (Oreg & Bayazit, 2009). In attempt to close this gap, Oreg and Bayazit (2009) developed a taxonomy focused on individual differences (e.g., personality, ability, temperament) as the shared underlying factors posited to lead to the use of cognitive heuristics and biases. They developed this taxonomy based on a systematic review of existing research providing evidence that individual differences such as general mental ability (GMA), personality, and motivational traits are related to performance on cognitive heuristics-and-biases tasks (Beauregard & Dunning, 2001; Lauriola & Levin, 2001; Mann et al., 2004; Newstead et al., 2004).

The taxonomy proposed by Oreg and Bayazit (2009), has the potential to advance scientific understanding of cognitive heuristics and biases by classifying biases into an organized schema so that future research is parsimonious and unified. However, the taxonomy lacks empirical support. This study provided a first step in evaluating the validity and utility of using individual differences to categorize cognitive biases through the testing of the Oreg and Bayazit (2009) taxonomy. Our subgoals included testing the relationship between the biases and their proposed categorization and testing whether the individual difference antecedents theorized by Oreg and Bayazit (2009) represented shared underlying mechanisms of biases.

Overall, the findings offered little validity evidence. Specifically, empirical relationships between bias categories did not align with the proposed taxonomy structure, and few of the hypothesized relationships between individual differences and biases were supported. Neuroticism, extraversion, openness to experience, working memory, and motivation did not predict performance on their respective heuristics-and-biases tasks with much certainty. These results are notably different from past research. For instance, previous research has found working memory to be related to cognitive bias (Del Missier et al., 2012; Engle, 2002), approach/avoidance temperament to be related to risk aversion, and personality factors like neuroticism to be negatively related to confidence judgments on general knowledge questions (e.g., Hancock et al., 1996). In addition, the results of this study were not consistent with past research demonstrating differences in rational decision-making tendencies (as measured by the A-DMC scale) based on broad personality factors (Weller et al., 2018).

A few encouraging findings did emerge, however. The pattern of correlations between biases within a category was more strongly positive than the pattern of correlations between biases from different categories for verification and simplification biases. These correlational patterns provided some evidence that Oreg and Bayazit's (2009) proposed grouping may be suitable. In addition, GMA was found to predict performance on simplification biases. Specifically, people with high GMA are *less* likely[7] to fall prey to biases. These results align with previous studies that have found cognitive abilities are related to performance on heuristics-and-biases tasks (e.g., Jackson et al., 2016).

In sum, little evidence was found to support relationships between individual differences and cognitive biases based on the taxonomy proposed by Oreg and Bayazit (2009). These results should not be taken to mean that the taxonomy is invalid; it is too early to determine that the taxonomic structure is not sufficient or not useful because our research only represents a single study. Validity evidence ought to be built on results from many studies. However, the study's null findings (e.g., lack of shared variance across cognitive heuristics-and-biases tasks) do underscore the criticality of future research in advancing cognitive bias research (Waller et al., 2006). Null findings are substantial contributions to existing research (Banks et al., 2016; Bosco et al., 2015; Landis et al., 2014). As such, there has been a recent acknowledgement of the importance of publication of null results because doing so is one of the most critical actions needed to advance our understanding of psychological phenomena (Banks et al., 2016; Landis et al., 2014). Findings that fail to produce significant or confirmatory results serve as fundamental pieces of evidence for the usefulness of the theory in question. After all, the crux of the scientific method and theory development is the attempt to falsify or disprove theories (Antonakis, 2017; Cucina & McDaniel, 2016).

Although the evidence from this study did not provide strong support for the taxonomy, we reason that the inconclusive results of this study are relevant and of critical import for the larger body of literature examining cognitive bias. These results inspire and point to future lines of research that are necessary for rigorously advancing the scientific underpinnings of cognitive heuristics and biases. Specifically, additional validity studies examining the quality of measurement and psychometric properties of heuristics-and-biases tasks ought to be conducted.

[7] The positive coefficient is due to the scoring of the measure. Higher scores equaled more correct answers (and therefore less bias).

If current methods of measurement are not adequate, the use of tools in any practical settings could be at best misleading and at worst harmful. Indeed, extant studies demonstrate that using measurement methods in practice or science before validity is established can lead to a number of problems including inconclusive inferences, lack of a testable model, and difficulties interpreting scores (Brunel et al., 2004; Fiedler et al., 2006; Greenwald et al., 2009; Schimmack, 2021). For example, the Implicit Association Test (IAT) became well-recognized and commonly used for diagnostic purposes prior to understanding and evaluating its psychometric properties. These measurement issues have rendered the body of literature using the IAT methodologically flawed and in turn dubious (Fiedler et al., 2006). We highly encourage researchers to prioritize validity studies and examination of the psychometric properties of cognitive heuristics-and-biases tasks.

Measurement Effects and Theoretical Implications

Through this research, we discovered, surprisingly, that the bias measures—identified based on wide-range use and consensus amongst researchers as preferred methods of measurement for cognitive bias—introduced a noteworthy amount of error and complexity in understanding the results. Similar arguments have been made in the fields of cognitive and social psychology regarding measurements such as the IAT as discussed in the previous section (e.g., Brunel et al., 2004; Greenwald et al., 2009; Schimmack, 2021). Measurement problems introduce limitations to empirical studies; yet, in this case, they ought to be considered as findings themselves. The data from this study revealed several empirical markers that the well-accepted bias tasks are not adequate measures of the constructs they purport to measure for the within-subjects research design. For instance, the items of the bias scales shared little variance and, therefore, internal consistency reliabilities were low. An examination of various items within the over/underconfidence measure (Bruine de Bruin et al., 2007), indicated that decision points within the scale had low correlations with one another. These low correlations could potentially indicate measurement error, which can negatively affect moderated multiple regression results (Aguinis & Gottfredson, 2010) or they could potentially indicate that over/underconfidence bias is highly context-dependent and traditional psychometric scales have shortcomings for measuring the bias (i.e., one should not expect different decision points to be related).

A handful of studies examining the measurement model of cognitive heuristics-and-biases tasks demonstrated that factors comprised from heuristics-and-biases tasks are uninterpretable and difficult to replicate across studies (Blacksmith, Behrend et al., 2019; Jackson et al., 2016; Weaver & Stewart, 2012). Although findings suggested that GMA predicted performance on simplification biases, it is critical to note that while GMA is theoretically distinct from heuristics-and-biases task performance, research has demonstrated that it is not empirically distinct (Blacksmith, Behrend, et al., 2019). The correlations between GMA and some heuristics-and-biases tasks were sufficiently high to denote construct overlap (Blacksmith, Behrend, et al., 2019; Blacksmith, Yang, et al., 2019). The observed strength of the relationship across studies is sufficiently high to suggest potential construct redundancy, a problematic condition for researchers (Le et al., 2010).

The measurement issues that arose in this study could be partially due to the historical purpose of the cognitive heuristics-and-biases tasks; they were originally designed for between-subjects research but were adapted to within-subjects designs to examine relationships with individual differences. The adaptation of measures for a within-subjects design may have altered the measurement in a way that changed the constructs being measured, thereby decreasing the validity of test score inferences.

The inadequate measurement does not render the study unworthy of dissemination, but in fact the opposite: the findings of this study are crucial for advancing the science of judgment and decision-making measurement. The measures we chose to use in this study have been used for decades in bias research and are highly cited (e.g., base rate and framing effects items developed in part by Nobel prize-winner, Daniel Kahneman). However, several of the measures used were originally developed as heuristics-and-biases tasks for use in between-subjects designs. Only recently have they been adapted for within-subjects designs (e.g., Bruine de Bruin et al., 2007, Stanovich et al., 2016).

Making conclusions about a taxonomy or identifying antecedents of cognitive heuristic and biases will prove difficult until the measurement of cognitive heuristics and biases improves for within-subjects research design and the measurement methods and theoretical constructs are distinguished from one another. Without the ability to conduct within-subjects research designs, research attempting to understand the real-world impact of cognitive biases will not be fruitful. Experimental studies are often impractical or unethical in settings such as the workplace or healthcare, two areas where the effects of biases are of interest.

Last, it begets the question of whether the growing number of cognitive bias research studies with within-subjects designs (e.g., Bruine de Bruin et al., 2007; Marcus-Blank et al., 2015; Stanovich et al., 2016) reached sound and credible conclusions. Sound measurement is the crux of science. Although the research examining if and how individual differences such as personality are meaningfully related to propensity to engage in cognitive bias is growing (e.g., Blacksmith, Yang et al., 2019; Bruine de Bruin et al., 2012; Cokely & Kelly, 2009; Jiang & Kleitman, 2015; Kleitman et al., 2019), we believe more research in this area should be done to advance our understanding. The discovery that many of the most used heuristics-and-biases tasks are not trustworthy measures, in part, contributes to the literature by bringing the reservation of whether we can claim these tasks as valid measurement to the forefront.

Thus, because this study used "well-established" tasks that have been used in numerous studies, the results are of foundational importance for understanding the broad conclusions that have been drawn from previous cognitive bias research. The unreliable measurement properties of "well-established" items and scales is concerning. As mentioned, the measurement error obscures our ability to interpret the results of this study. It is not possible to draw credible conclusions from any scientific study without strong measurement.

Recommendations for Cognitive Bias Measurement

We offer two main suggestions for the cognitive bias literature considering the results of this study. First, the construct space and nomological network for cognitive heuristics and biases need to be better defined in order to develop sound measures. To elaborate, because of the generally consistent relationship between GMA and cognitive bias (i.e., empirical redundancy), it is unclear what heuristics-and-biases tasks are measuring. Are heuristics-and-biases tasks measuring cognitive heuristics and bias, or are they measuring GMA, numerical ability, and/or reasoning ability? It is possible that when measured via traditional psychometric assessments, heuristics-and-biases tasks are just deficient measures of GMA or measures of specific cognitive abilities (e.g., numerical ability). Currently, definitions of many of the biases are confounded with the method used to measure the bias. To effectively measure any psychological construct, researchers need to clearly define the theoretical construct, including how it is distinct from similar constructs, and distinguish between the theoretical construct and the observed measurement methods.

Second, measurement methods of cognitive bias (once adequately defined) must be improved. We argue that a focus should be placed on the cognitive process of how biases arise as opposed to responses given on a traditional psychometric assessment. Traditional psychometrics assessments likely function differently in within-subjects designs because they only offer researchers the end result (i.e., the decision-maker's final choice) and do not capture *how* the decision-maker reached that result (i.e., use of heuristics). Future research examining the relationship between individual differences and cognitive bias should measure the actual *cognitive processes* used to reach a decision, not the final decision product of a test item. One suggestion to improve measurement of cognitive biases is to use a think-aloud protocol. Using a method that would allow people to walk researchers through their decision making and thought processes could provide a better understanding of the thought process in which one engages and, consequently, what is actually being measured.

Third, to advance the field, the nomological network of cognitive bias needs to be better specified. For example, cognitive bias and other similar constructs (e.g., GMA, rational thinking, decision-making strategy) need to be clearly distinguished. If the focus is placed on the actual cognitive processes (not the outcome of the process) it will likely be easier to make theoretical arguments for their distinction with cognitive ability. When a clear distinction between the constructs is made, it can help avoid construct redundancy.

Practical Implications

Although these data represent a test of a taxonomy rather than a real-world application, there are practical implications in the near- and long-term. As researchers continue to refine and build the nomological network surrounding cognitive heuristics and biases, more can be done to incorporate information about biases into military training. A number of biases could affect different steps of the military decision-making process (MDMP; Janser, 2007). For example, confirmation bias could affect judgments made during mission analysis and overconfidence could affect judgments about which course of action to pursue. Moreover, particularly because the MDMP is not used when there is limited time (Janser, 2007), it is important to make Soldiers and officers aware of cognitive heuristics that they may be using when making decisions under time pressure. One approach to this training could include a focus on metacognition to increase reliance on analytical thinking (System 2) rather than intuitive thinking (System 1; Rodman, 2015). However, although they receive training about the MDMP, Soldiers and officers must still make a large number of decisions that rely on intuitive judgment (due to frequent uncertainty and time-bound decisions, for example). Therefore, a focus on training to refine intuitive decision making and prevent bias in those situations could also be beneficial (Rodman, 2015).

Organizations are currently taking active steps to prevent cognitive bias by developing interventions to train employees to avoid cognitive heuristics and in turn avoid biases and make better decisions (e.g., DOJ, 2015; NRC, 2015; Tispursky, 2018). However, there remains a large gap in our understanding of how biases manifest, leaving organizations with limited knowledge of how to develop effective training programs (Rodman, 2015). Studies such as this are the first step in advancing our understanding of why people engage in cognitive heuristics and how we may be able to prevent them.

Study Limitations

Although we tested the bias categorization proposed by Oreg and Bayazit (2009) we acknowledge, in hindsight, that the notion and appropriateness of testing a taxonomy assumes the presence of sound measurement built on clear definitions. However, it is unclear if heuristics-and-biases tasks represent reflective indicators of a latent factor such as cognitive ability (Blacksmith, Behrend, et al., 2019; Jackson et al., 2016) or are formative indicators of circumstances and experience (e.g., tacit knowledge, exposure to bias items in the past, motivation) that produce a bias score. As such, the moderated multiple regression analyses should be interpreted with caution given the broader measurement problem. As we mentioned above, the construct theory behind biases is underdeveloped and the literature has mixed findings. For instance, Bruine de Bruin et al. (2007) deemed their A-DMC as highly valid.

Another limitation of the study is the uniqueness of the Army sample. U.S. Army Soldiers are trained in the MDMP (U.S. Department of the Army, 2015). Some have suggested that training in the MDMP does not remove the possibility of engaging in cognitive bias (Janser, 2007). At this point, it is unknown how results might generalize to people with other types of decision-making training or to people without any decision-making training.

Finally, using an individual differences measure of working memory prior to engagement in the heuristics-and-biases tasks could explain the mixed findings between working memory and cognitive bias. It is possible that situational measures of working memory (i.e., state-based instead of trait-based) would have been more appropriate because the amount of working memory available is likely to shift frequently depending on the level of cognitive load the task generates. In future research cognitive capacity should be measured *during* the process of responding to cognitive heuristics-and-biases tasks. Measuring cognitive load during response to heuristics-and-biases tasks could be collected with physiological metrics or digital behaviors (e.g., Brünken et al., 2003) to provide a more accurate measure of working memory.

Conclusion

Cognitive heuristics and cognitive biases are undoubtedly a component of information processing and decision-making; there are decades of research demonstrating a large number of biases and their ubiquity. The logical next step to advance this research is to understand the antecedents and consequences of cognitive biases. However, with hundreds of identified biases and measurement problems, this will be a daunting task. Although the data in this study did not provide strong support for the validity of the taxonomy (Oreg & Bayazit, 2009), we encourage researchers to continue these taxonomic investigations by determining the magnitude of relationships and identifying boundary conditions in order to continue building validity evidence. Our study along with previous research on similar measures (e.g., Blacksmith, Yang et al., 2019; Erceg & Bubić, 2017; Thomson & Oppenheimer, 2016) call the current measurement methods of heuristics and biases into question. We strongly advocate that future research begin by developing and validating cognitive bias measures for use in within-subjects research designs.

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Appendix A

Validity Evidence Summary

Evidence	Proposed Support	Summary of Results	Support
Evidence A1	Relationships between heuristics-and-biases tasks within a category are positive and stronger than relationships between heuristics and biases categories.	Correlations within categories were greater than average correlation between categories for verification and simplification biases.	Moderate Partial Support
Evidence A2	A 3-factor structure will emerge from the heuristics-and-biases tasks (i.e., verification, simplification, and regulation biases).	Inconsistent grouping of bias category scale scores and items.	Weak Partial Support
Evidence B	Neuroticism is positively related to manifestation of verification biases.	Trends in the predicted direction but trivial effect sizes.	Very Weak Support
Evidence C	Openness to experience is related to the manifestation of simplification biases.	Openness to experience had trivial effects in opposite the expected direction.	Not Supported
Evidence D	GMA is related to the manifestation of simplification biases.	GMA positively predicted simplification biases.	Supported
Evidence E	Extraversion is related to the manifestation of regulation biases.	E1: Trivial effects for framing (gain) and trivial effects in opposite the predicted direction for the certainty effect.	Very Weak Support
		E2: Trivial effects in the opposite the predicted direction for framing (loss).	Not Supported
Evidence F	Neuroticism is related to manifestation of regulation biases.	F1: Effects in the predicted direction for framing (loss) and trivial effects in opposite the predicted direction for the certainty effect.	Partial Support
		F2: Trivial effects in opposite the predicted direction for framing (gain).	Not Supported
Evidence G	Working memory is negatively related to performance on heuristics-and-biases tasks.	Working memory negatively predicted under/overconfidence and positively predicted belief bias and base rate neglect. For the other biases, there were negligible relationships.	Weak Partial Support
Evidence H	Test-taking motivation interacts with individual differences to predict performance on heuristics-and-biases tasks.	No meaningful interactions were present.	Not Supported

Note. Simplification biases were scored such that higher scores meant less bias.

Appendix B

Example Questions of Heuristics-and-Biases Tasks

Verification Bias (Motivation: Achieve consistency)

Hindsight Bias - Perceiving events that have already happened as being more probable

Example Question: Select the word that comes closest to the meaning of the word in capital letters. Indicate how confident you are in your response.

EMANATE

(1) Populate (2) Free (3) Prominent (4) Rival (5) Come

[Confidence in accuracy: 20% Just Guessing to 100% Absolutely Sure]

Under/overconfidence - "How well participants recognize the extent of their own knowledge" (Bruine de Bruin et al., 2007, p. 942)

Example Question: Read each question and choose the best answer. Indicate how confident you are in your response.

The 4th planet from the sun is:

(1) Jupiter (2) Saturn (3) Pluto (4) Earth (5) Mars (6) Venus (7) None of these

[Confidence in accuracy: 10% Just Guessing to 100% Absolutely Sure]

Simplification Bias (Motivation: Comprehending reality)

Belief Bias - Tendency to evaluate deductive arguments based on whether or not the conclusion sounds believable rather than on the basis of logic (Evans et al., 1983; Teovanović et al., 2015)

Example Question: Decide if the conclusion *follows logically from the premises*.

Premise 1: All things that are smoked are good for the health.

Premise 2: Cigarettes are smoked.

Conclusion: Cigarettes are good for the health.

Base Rate - Reliance on representativeness information instead of base rate and probability information when making a decision (Tversky & Kahneman, 1983)

Example Question: Circle choice with best answer.

A study had 1000 participants. Among the participants there were 25 men and 975 women. Sam is a randomly chosen participant in this study. Sam is 23 years old, graduated as a mechanical engineer and enjoys going out with friends, likes drinking beer and is a fan of hard rock music. Which option is more probable?

Option 1: Sam is a woman

Option 2: Sam is a man

Regulation Bias (Motivation: Approaching pleasure and avoiding pain)

Framing Effects - Tendency to prefer certainty and feel displeasure when the probability of gains is reduced (Tversky & Kahneman, 1986)

Example Question (Gain Frame): Choose between two options on a scale ranging from 1 (Option A) to 6 (Option B). Choose the number that best reflects your relative preference between the two options.

Imagine that recent evidence has shown that a pesticide is threatening the lives of 1,200 endangered animals. Two response options have been suggested:

If **Option A** is used, 600 animals will be saved for sure.

If **Option B** is used, there is a 75% chance that 400 animals will be lost, and a 25% chance that 1,200 animals will be lost.

Certainty Effect - Comparison of choices in certain and uncertain situations; level of risk averseness affects choices

Example Question:

Choose between Option A and Option B.

Option A: One million dollars for sure.

Option B: .89 probability of one million dollars
.10 probability of five million dollars
.01 probability of nothing

Appendix C

SIOP Poster Presentations

Can Cognitive Heuristics-and-Biases be Classified by Shared Causal Mechanisms?

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Consortium of Universities of the Washington Metropolitan Area

RESEARCH QUESTION

Can cognitive biases be systematically classified based on shared causal mechanisms according to the taxonomy proposed by Oreg and Bayazit (2009)?

BACKGROUND

- An estimated 175 cognitive biases have been identified.
- Unfortunately, the scientific literature on cognitive bias remains disjointed due to a lack of an organizing framework. If research is to advance, an organizing framework for cognitive bias must be established.
- Oreg and Bayazit (2009) proposed a taxonomy of cognitive biases based on shared causal mechanisms of biases.

Purpose: Empirically test the taxonomic propositions set forth by Oreg and Bayazit (2009).

ANALYTIC STRATEGY

Evaluate correlations within and between biases:

1. Correlations between biases
2. Patterns of correlations between biases and individual differences.

Why not factor analysis?

- Assumption that observed measures reflect an underlying, latent factor (Kim & Mueller, 1978)
- Scores on cognitive heuristics-and-biases tasks are observed (measured) variables

METHOD

469 active duty U.S. Army Soldiers

- 134 cases removed (inappropriate quality control item responses, not finishing, failure to follow instructions)
- Age_{mean} = 30.63 years (SD = 6.42)
- 77% male, 63% Caucasian

Measures from/adapted from:

Biases	
Teovanović et al. (2015)	Hindsight Bias
Marcus-Blank et al. (2015)	Belief Bias, Base Rate Neglect, Certainty Effect
Bruine de Bruin et al. (2007)	Under/overconfidence, Framing
Individual Differences	
General Mental Ability	ICAR Sample Test (Condon & Revelle, 2014),
Personality	Big 5 Inventory from IPIP (Goldberg, 1992, 1999; Goldberg et al., 2006)

Table 1
Summary of Oreg and Bayazit's (2009) Taxonomy of Cognitive Biases

Bias Type	Description	Motivation	Example Bias	Definition	Example Question
Verification	Distortions in perceptions of self and reality	Achieve consistency	Hindsight Bias	Perceiving events that have already happened as being more probable	EMANATE (1) Populate (2) Free (3) Prominent (4) Rival (5) Come
Simplification	Way of analyzing information	Comprehending reality	Belief Bias	Tendency to evaluate deductive arguments based on whether or not the conclusion sounds believable rather than on the basis of logic (Evans et al., 1983; Teovanović et al., 2015)	Premise 1: All things that are smoked are good for the health. Premise 2: Cigarettes are smoked. Conclusion: Cigarettes are good for the health.
Regulation	Non-normative decisions and behaviors	Approaching pleasure and avoiding pain	Certainty Effect	Tendency to prefer certainty and feel displeasure when the probability of gains is reduced (Tversky & Kahneman, 1986)	Option A: A sure gain of $240 Option B: 25% chance to gain $1000 and 75% chance to gain nothing Option A: a sure loss of $750 Option B: 75% chance to lose $1000 and 25% chance to lose nothing

Table 2
Correlations among Study Variables

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1. Hindsight (V)	-											
2. Confidence (V)	**.37***	-										
3. Belief Bias (S)	-.22*	-.29*	-									
4. Base Rate (S)	-.07	-.32*	**.46***	-								
5. Framing (R)	.02	-.10*	.15*	.10*	-							
6. Certainty (R)	.03	.05	.07	.00	**.05**	-						
7. GMA	-.24*	-.41*	.55*	.48*	.14*	.02	-					
8. Neuroticism	.03	.09*	-.07	-.10*	-.03	-.03	-.04	-				
9. Conscientiousness	.04	-.11*	-.06	.03	-.07	.05	.00	-.49*	-			
10. Extraversion	.07	.03	-.03	-.04	.01	.00	-.01	-.45*	.32*	-		
11. Openness	-.20*	-.18*	.10*	.05	.00	.02	.17*	-.16*	.08	.28*	-	
12. Agreeableness	-.03	.00	.02	.01	-.03	.05	.10*	-.25*	.40*	.25*	.25*	-
13. Gender	-.04	.16*	-.14*	-.15*	-.09	-.01	-.14*	.05	.06	-.04	-.02	.11*

RESULTS

Compare Correlations Between and Within Bias Categories:

- Correlation between Verification biases (r = .37) stronger than the average correlation (r = -.11) of Verification biases with Simplification and Regulation biases
  - Partial Support
- Correlation between Simplification biases (r = .46) stronger than the average correlation (r = -.07) of Simplification biases with Verification and Regulation biases
  - Partial Support
- Correlation between Regulation biases was negligible (r = .05); similar negligible average correlation (r = .04) with Verification and Simplification biases

RESULTS CONTINUED

Examine Patterns of Correlations Between Biases and Individual Differences

- Neuroticism should be related to Verification biases
  - Under/overconfidence – r = .09
  - Hindsight – r = .03
- Openness should be related to Simplification biases
  - Belief Bias – r = .10
  - Base Rate – r = .05
- Neuroticism, Openness, and Extraversion should be related to Regulation biases
  - Neuroticism average correlation – r = -.03
  - Openness average correlation – r = .01
  - Extraversion average correlation – r = .005
- GMA should be related to Verification biases
  - Belief Bias – r = .55
  - Base Rate – r = .48

  Partial Support
- GMA should be related to Simplification biases
  - Hindsight – r = -.24
  - Base Rate – r = -.41

  Partial Support
- GMA should be related to Regulation biases
  - Framing – r = .14
  - Certainty Effect – r = . 02

DISCUSSION

- Partial support for Oreg and Bayazit's (2009) taxonomy.
- GMA, but not personality, was related to the tendency to engage in cognitive bias.
  - Unexpected negative relationship between GMA and Simplification biases
- Contributed by beginning to classify large amount of unaccounted for systematic variance in heuristics-and-biases task performance
- Limitations:
  - Army sample - Soldiers are instructed to execute the military decision-making process (Department of the Army, 2015)
  - Only assessed two biases from each category
  - Regulation biases had limited variance and range restriction

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Individual Difference Determinants of Heuristics-and-Biases Task Performance

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Consortium of Universities of the Washington Metropolitan Area

RESEARCH QUESTION

Do individual differences predict cognitive bias?

BACKGROUND

- People use cognitive heuristics every day to make decisions and decrease cognitive load.
- Sometimes, the use of heuristics leads to biased decision making.
- Organizations have begun to develop interventions to train employees how to make unbiased decisions.
- Individual differences may predict whether and when people will engage in cognitive bias (Oreg & Bayazit, 2009).
- For example:
  - Working memory – Working memory provides the computing power necessary to override the intuitive response and engage in effortful cognitive processing (Barrett et al., 2004; Quayle & Ball, 2000).
  - General mental ability – Logical (vs. intuitive) evaluation of arguments is more likely if greater cognitive resources are available (Oreg & Bayazit, 2009).
  - Intellect – A desire to handle challenging or difficult material (Costa & McCrae, 1992) may decrease the likelihood of bias susceptibility.
- Motivation may act as a moderator that encourages some people to overcome automatic processing (i.e., the use of heuristics) and engage in effortful, analytical processing.

METHOD

469 active duty U.S. Army Soldiers

- 134 cases removed (inappropriate quality control item responses, not finishing, failure to follow instructions)
- Age_{mean} = 30.63 years (SD = 6.42)
- 77% male, 63% Caucasian

Measures from/adapted from:

Biases	
Hindsight Bias	Teovanović et al. (2015)
Belief Bias	Marcus-Blank et al. (2015)
Framing Effects	Bruine de Bruin et al. (2007)
Individual Differences	
General Mental Ability	ICAR Sample Test (Condon & Revelle, 2014),
Personality	Big 5 Inventory from IPIP (Goldberg, 1992, 1999; Goldberg et al., 2006)

Table 1
Moderated Multiple Regression Results for Hindsight Bias

	b	SE	β	*t*	*p*	95% CI for b		b	SE	β	*t*	*p*	95% CI for b	
(constant)	3.63	1.01		3.60	<.001	1.64	5.62	.23	4.46		.05	.96	-8.56	9.01
Step 1														
Self-Consciousness	-.11	.14	-.05	-.78	.44	-.40	.17	.32	1.25	.14	.26	.80	-2.15	2.79
Working Memory	-.01	.02	-.03	-.50	.62	-.05	.03	.10	.14	.35	.67	.51	-.19	.38
Motivation	.14	.28	.03	.51	.61	-.41	.69	1.11	1.26	.27	.88	.38	-1.37	3.59
Step 2														
Self-Conscious × Motivation								-.12	.35	-.20	-.35	.73	-.81	.57
Working Memory × Motivation								-.03	.04	-.47	-.73	.46	-.11	.05
R^2							.00							.01
F							.33							.33
df						3	246						5	244
ΔR^2, *p*													.00	.72

Note. n = 250. SE = standard error. CI = confidence interval.

Table 2
Moderated Multiple Regression Results for Belief Bias

	b	SE	β	*t*	*p*	95% CI for b		b	SE	β	*t*	*p*	95% CI for b	
(constant)	-.01	.96		-.02	.99	-1.90	1.87	.08	4.10		.02	.99	-7.97	8.13
Step 1														
Intellect	.22	.15	.07	1.54	.12	-.06	.51	1.10	1.04	.34	1.06	.29	-.94	3.13
GMA	.37	.03	.54	10.94	<.001	.31	.44	-.03	.27	-.05	-.13	.90	-.56	.49
Working Memory	.01	.02	.03	.65	.52	-.02	.05	-.00	.15	-.01	-.02	.99	-.29	.29
Motivation	-.05	.28	-.01	-.19	.85	-.60	.49	-.08	1.19	-.01	-.07	.95	-2.41	2.26
Step 2														
Intellect × Motivation								-.25	.29	-.34	-.86	.39	-.83	.32
GMA × Motivation								.12	.08	.65	1.53	.13	-.03	.26
Working Memory × Motivation								.00	.04	.05	.10	.92	-.08	.09
R^2							.33							.33
F							45.86							26.65
Df						4	380						7	377
ΔR^2, *p*													.01	.38

Note. n = 385. SE = standard error. CI = confidence interval.

Table 3
Moderated Multiple Regression Results for Framing Effects

	b	SE	β	*t*	*p*	95% CI for b		b	SE	β	*t*	*p*	95% CI for b	
(constant)	2.85	.48		5.89	<.001	1.90	3.80	4.68	2.59		1.81	.07	-.42	9.77
Step 1														
Excitement-Seeking	-.10	.07	-.07	-1.43	.16	-.23	.04	-.12	.52	-.09	-.23	.82	-1.13	.90
Immoderation	-.08	.07	-.06	-1.15	.25	-.21	.05	-.05	.55	-.04	-.08	.93	-1.13	.90
Working Memory	-.00	.01	-.03	-.53	.60	-.02	.01	-.08	.06	-.57	-1.40	.16	-.20	.03
Motivation	.20	.12	.09	1.69	.09	-.03	.43	-.33	.73	-.15	-.46	.65	-1.77	1.11
Step 2														
Excitement-Seeking × Motivation								.01	.15	.02	.05	.96	-.28	.29
Immoderation × Motivation								-.01	.15	-.02	-.05	.96	-.31	.30
Working Memory × Motivation								.02	.02	.66	1.34	.18	-.01	.06
R^2							.02							.02
F							1.74							1.25
df						4	377						7	374
ΔR^2, *p*													.01	.61

Note. n = 382. SE = standard error. CI = confidence interval.

HYPOTHESES & RESULTS

H1: **Working memory** will be negatively related to performance on heuristics-and-biases tasks.
Not Supported

H2: **Self-consciousness** will be positively related to the manifestation of **hindsight bias**.
Not Supported

H3a: **General mental ability** will be negatively related to the manifestation of **belief bias**.
Supported

H3b: **Intellect** will be negatively related to the manifestation of **belief bias**.
Not Supported

H4a: **Excitement-seeking** will be negatively related to **framing effects**.
Not Supported

H4b: **Immoderation** will be positively related to **framing effects**.
Not Supported

H5: **Test-taking motivation** will moderate the relationships between individual differences and cognitive biases such that there will be less bias when individuals have higher motivation.
Not Supported

DISCUSSION

- Tested taxonomic propositions from Oreg and Bayazit (2009)
- Working memory did not predict cognitive bias, contrary to past research (Del Missier et al., 2012; Engle, 2002)
- Our results suggested that only GMA predicted cognitive bias
  - Contrary to other past research that has found personality to predict cognitive bias
- Motivation did not interact with individual differences to predict cognitive bias
- Remains important to report null findings, as they contribute to existing research (e.g., Banks et al., 2016, Landis et al., 2014)
- Future research:
  - Explore different measures of working memory
  - Improve/refine cognitive measures, study using between- and within-subjects measures

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Appendix D

Moderated Multiple Regression Results

Table D1

Moderated Multiple Regression Results for Hindsight Bias

	Constant	Age	Edu	W. Mem	Mot	Neu	Neu x Mot
Step 1: $F(2, 223) = .01$, $p = .99$, $R^2 < .001$							
b	3.72	-.002	.004				
SE	.76	.02	.09				
β		-.01	.003				
t	4.90*	-.13	.05				
L	2.22	-.04	-.17				
U	5.22	.03	.18				
Tol		.97	.97				
VIF		1.03	1.03				
Step 2: $F(4, 221) = .13$, $p = .97$, $R^2 = .002$, $\Delta R^2 = .002$, $p = .79$							
b	3.86	-.004	.002	-.01	.06		
SE	1.10	.02	.09	.02	.19		
β		-.02	.002	-.05	.02		
t	3.52*	-.22	.02	-.69	.33		
L	1.70	-.04	-.17	-.05	-.32		
U	6.03	.03	.17	.03	.44		
Tol		.94	.96	.87	.87		
VIF		1.06	1.05	1.15	1.15		
Step 3: $F(5, 220) = .13$, $p = .99$, $R^2 = .003$, $\Delta R^2 = .001$, $p = .72$							
b	3.65	-.004	.003	-.01	.06	.08	
SE	1.24	.02	.09	.02	.19	.22	
β		-.02	.003	-.05	.02	.03	
t	2.94*	-.22	.04	-.64	.33	.36	
L	1.21	-.04	-.17	-.05	-.32	-.36	
U	6.10	.03	.18	.03	.44	.52	
Tol		.94	.95	.86	.87	.98	
VIF		1.06	1.05	1.17	1.15	1.02	
Step 4: $F(6, 219) = .14$, $p = .99$, $R^2 = .004$, $\Delta R^2 = .001$, $p = .65$							
b	2.38	-.01	.004	-.01	.39	.70	-.15
SE	3.09	.02	.09	.02	.75	1.38	.34
β		-.02	.003	-.05	.15	.21	-.22
t	.77	-.29	.04	-.64	.52	.51	-.45
L	-3.71	-.04	-.17	-.05	-1.09	-2.02	-.82
U	8.46	.03	.18	.03	1.87	3.42	.52
Tol		.92	.95	.86	.06	.03	.02
VIF		1.09	1.05	1.17	17.38	38.30	51.97

Note. SE = standard error. Tol = Tolerance. VIF = Variance Inflation Factor. * $p < .05$. L = lower bound of 95% confidence interval for b. U = upper bound of 95% confidence interval for b. Edu = Education. W. Mem = working memory. Mot = motivation. Neu = neuroticism.

Table D2

Moderated Multiple Regression Results for Under/overconfidence

	Constant	Age	Edu	W. Mem	Mot	Neu	Neu x Mot
Step 1: $F(2, 344) = 3.85$, $p = .02$, $R^2 = .02$							
b	-71.84	.04	-1.18				
SE	4.01	.10	.45				
β		.02	-.14				
t	-17.93*	.39	-2.64*				
L	-79.72	-.16	-2.06				
U	-63.96	.23	-.30				
Tol		.97	.97				
VIF		1.03	1.03				
Step 2: $F(4, 342) = 6.42$, $p < .001$, $R^2 = .07$, $\Delta R^2 = .05$, $p < .001$							
b	-56.56	-.03	-.99	-.32	-1.57		
SE	5.71	.10	.44	.10	.98		
β		-.02	-.12	-.18	-.09		
t	-9.91*	-.33	-2.25*	-3.29*	-1.60		
L	-67.79	-.23	-1.85	-.51	-3.49		
U	-45.33	.16	-.12	-.13	.36		
Tol		.94	.96	.89	.90		
VIF		1.06	1.04	1.12	1.11		
Step 3: $F(5, 341) = 5.49$, $p < .001$, $R^2 = .07$, $\Delta R^2 = .01$, $p = .19$							
b	-60.69	-.03	-.97	-.31	-1.50	1.53	
SE	6.52	.10	.44	.10	.98	1.17	
β		-.02	-.12	-.18	-.08	.07	
t	-9.31*	-.28	-2.21*	-3.20*	-1.53	1.31	
L	-73.51	-.22	-1.83	-.50	-3.42	-.77	
U	-47.86	.17	-.11	-.12	.43	3.82	
Tol		.94	.96	.89	.90	.99	
VIF		1.06	1.04	1.13	1.11	1.01	
Step 4: $F(6, 340) = 4.92$, $p < .001$, $R^2 = .08$, $\Delta R^2 = .01$, $p = .16$							
b	-82.25	-.05	-.98	-.31	3.91	11.56	-2.46
SE	16.60	.10	.44	.10	3.95	7.20	1.74
β		-.03	-.12	-.17	.22	.52	-.53
t	-4.96*	-.50	-2.24*	-3.16*	.99	1.61	-1.41
L	-114.90	-.24	-1.84	-.50	-3.87	-2.60	-5.88
U	-49.60	.15	-.12	-.12	11.69	25.72	.97
Tol		.92	.96	.89	.06	.03	.02
VIF		1.09	1.04	1.13	18.22	38.52	51.87

Note. SE = standard error. Tol = Tolerance. VIF = Variance Inflation Factor. * $p < .05$. L = lower bound of 95% confidence interval for b. U = upper bound of 95% confidence interval for b. Edu = Education. W. Mem = working memory. Mot = motivation. Neu = neuroticism.

Table D3

Moderated Multiple Regression Results for Belief Bias

	Constant	Age	Edu	W. Mem	Mot	Open	GMA	Open x Mot	GMA x Mot
Step 1: $F(2, 344) = 18.52$, $p < .001$, $R^2 = .10$									
b	5.50	-.10	.29						
SE	.86	.02	.10						
β		-.24	.16						
t	6.39*	-4.70*	3.03*						
L	3.81	-.14	.10						
U	7.19	-.06	.48						
Tol		.97	.97						
VIF		1.03	1.03						
Step 2: $F(4, 342) = 15.01$, $p < .001$, $R^2 = .15$, $\Delta R^2 = .05$, $p < .001$									
b	2.18	-.08	.25	.08	.26				
SE	1.22	.02	.09	.02	.21				
β		-.20	.14	.21	.07				
t	1.79	-3.98*	2.64*	3.88*	1.26				
L	-.22	-.13	.06	.04	-.15				
U	4.58	-.04	.43	.12	.68				
Tol		.94	.96	.89	.90				
VIF		1.06	1.04	1.12	1.11				
Step 3: $F(6, 340) = 26.47$, $p < .001$, $R^2 = .32$, $\Delta R^2 = .17$, $p < .001$									
b	2.93	-.06	.10	.01	-.04	-.19	.35		
SE	1.32	.02	.09	.02	.19	.27	.04		
β		-.14	.06	.02	-.01	-.03	.49		
t	2.22*	-3.00*	1.19	.42	-.20	-.72	9.17*		
L	.34	-.10	-.07	-.03	-.42	-.72	.27		
U	5.53	-.02	.27	.05	.34	.33	.42		
Tol		.92	.92	.76	.86	.94	.69		
VIF		1.09	1.09	1.32	1.17	1.06	1.45		
Step 4: $F(8, 338) = 20.79$, $p < .001$, $R^2 = .33$, $\Delta R^2 = .01$, $p = .06$									
b	-3.71	-.06	.09	.01	1.66	2.46	.03	-.67	.08
SE	5.13	.02	.09	.02	1.28	1.48	.19	.37	.05
β		-.14	.05	.02	.42	.43	.04	-.79	.53
t	-.72	-2.94*	1.03	.35	1.30	1.67	.13	-1.81	1.69
L	-13.80	-.09	-.08	-.03	-.86	-.45	-.36	-1.41	-.01
U	6.38	-.02	.26	.05	4.18	5.37	.41	.06	.17
Tol		.92	.89	.75	.02	.03	.03	.01	.02
VIF		1.09	1.12	1.34	51.94	33.02	38.69	94.71	48.63

Note. SE = standard error. Tol = Tolerance. VIF = Variance Inflation Factor. * $p < .05$. L = lower bound of 95% confidence interval for b. U = upper bound of 95% confidence interval for b. Edu = Education. W. Mem = working memory. Mot = motivation. Open = openness to experience. GMA = general mental ability.

Table D4

Moderated Multiple Regression Results for Base Rate Neglect

	Constant	Age	Edu	W. Mem	Mot	Open	GMA	Open x Mot	GMA x Mot
Step 1: *F*(2, 343) = 14.70, *p* < .001, R^2 = .08									
b	3.34	-.04	.42						
SE	.80	.02	.09						
β		-.10	.25						
t	4.15*	-1.90	4.70*						
L	1.76	-.08	.25						
U	4.92	.001	.60						
Tol		.97	.97						
VIF		1.03	1.03						
Step 2: *F*(4, 341) = 14.16, *p* < .001, R^2 = .14, ΔR^2 = .06, *p* < .001									
b	.15	-.02	.38	.09	.20				
SE	1.13	.02	.09	.02	.19				
β		-.06	.22	.24	.06				
t	.13	-1.09	4.35*	4.45*	1.03				
L	-2.08	-.06	.21	.05	-.18				
U	2.38	.02	.55	.12	.58				
Tol		.95	.96	.89	.90				
VIF		1.06	1.04	1.12	1.11				
Step 3: *F*(6, 339) = 19.65, *p* < .001 , R^2 = .26, ΔR^2 = .12, *p* < .001									
b	1.36	-.001	.28	.03	-.004	-.38	.26		
SE	1.27	.02	.08	.02	.19	.26	.04		
β		-.002	.16	.08	-.001	-.07	.41		
t	1.07	-.04	3.30*	1.57	-.02	-1.48	7.25*		
L	-1.14	-.04	.11	-.01	-.37	-.89	.19		
U	3.87	.04	.44	.07	.36	.13	.34		
Tol		.92	.92	.76	.86	.94	.69		
VIF		1.08	1.09	1.32	1.17	1.06	1.45		
Step 4: *F*(8, 337) = 15.24, *p* < .001, R^2 = .27, ΔR^2 = .01, *p* = .18									
b	-7.01	.002	.28	.03	2.13	2.23	.21	-.67	.01
SE	4.96	.02	.09	.02	1.24	1.43	.19	.36	.05
β		.004	.17	.08	.58	.42	.33	-.84	.09
t	-1.41	.08	3.34*	1.42	1.72	1.56	1.13	-1.85	.29
L	-16.77	-.04	.12	-.01	-.30	-.59	-.16	-1.38	-.08
U	2.76	.04	.45	.07	4.57	5.04	.58	.04	.10
Tol		.92	.89	.75	.02	.03	.03	.01	.02
VIF		1.09	1.13	1.34	51.96	32.88	38.68	94.44	48.61

Note. SE = standard error. Tol = Tolerance. VIF = Variance Inflation Factor. * *p* < .05. L = lower bound of 95% confidence interval for b. U = upper bound of 95% confidence interval for b. Edu = Education. W. Mem = working memory. Mot = motivation. Open = openness to experience. GMA = general mental ability.

Table D5

Moderated Multiple Regression Results for Framing (Gain)

	Constant	Age	Edu	W. Mem	Mot	Extra	Neu	Extra x Mot	Neu x Mot
Step 1: $F(2, 344) = .001$, $p = .999$, $R^2 < .001$									
b	2.78	<.001	-.002						
SE	.31	.01	.03						
β		-.002	-.003						
t	9.05*	-.03	-.05						
L	2.17	-.02	-.07						
U	3.38	.02	.07						
Tol		.97	.97						
VIF		1.03	1.03						
Step 2: $F(4, 342) = .69$, $p = .60$, $R^2 = .008$, $\Delta R^2 = .008$, $p = .25$									
b	2.37	<.001	-.01	-.004	.13				
SE	.45	.01	.03	.01	.08				
β		.003	-.01	-.03	.09				
t	5.30*	.06	-.19	-.52	1.66				
L	1.49	-.02	-.07	-.02	-.02				
U	3.25	.02	.06	.01	.28				
Tol		.94	.96	.89	.90				
VIF		1.06	1.04	1.12	1.11				
Step 3: $F(6, 340) = .59$, $p = .74$, $R^2 = .01$, $\Delta R^2 = .002$, $p = .68$									
b	1.92	.001	-.003	-.003	.12	.06	.09		
SE	.74	.01	.04	.01	.08	.11	.10		
β		.01	-.01	-.03	.09	.03	.05		
t	2.60*	.18	-.09	-.45	1.59	.49	.87		
L	.47	-.01	-.07	-.02	-.03	-.17	-.11		
U	3.38	.02	.07	.01	.28	.28	.29		
Tol		.91	.94	.89	.87	.75	.79		
VIF		1.11	1.06	1.13	1.15	1.34	1.27		
Step 4: $F(8, 338) = .95$, $p = .47$, $R^2 = .02$, $\Delta R^2 = .012$, $p = .13$									
b	-2.03	-.001	-.003	-.003	1.10	.41	1.35	-.09	-.31
SE	3.27	.01	.04	.01	.79	.65	.65	.16	.16
β		-.01	-.01	-.02	.82	.22	.80	-.32	-.88
t	-.62	-.12	-.09	-.36	1.39	.63	2.07*	-.54	-1.96
L	-8.46	-.02	-.07	-.02	-.46	-.87	.07	-.40	-.62
U	4.40	.02	.07	.01	2.66	1.68	2.63	.23	.001
Tol		.89	.94	.88	.01	.02	.02	.01	.02
VIF		1.13	1.07	1.13	118.81	43.05	51.30	119.95	68.79

Note. SE = standard error. Tol = Tolerance. VIF = Variance Inflation Factor. * $p < .05$. L = lower bound of 95% confidence interval for b. U = upper bound of 95% confidence interval for b. Edu = Education. W. Mem = working memory. Mot = motivation. Extra = extraversion. Neu = neuroticism.

Table D6

Moderated Multiple Regression Results for Framing (Loss)

	Constant	Age	Edu	W. Mem	Mot	Extra	Neu	Extra x Mot	Neu x Mot
Step 1: *F*(2, 339) = 5.24, *p* = .006, R^2 = .03									
b	2.73	.03	-.04						
SE	.35	.01	.04						
β		.16	-.05						
t	7.76*	2.91*	-.94						
L	2.04	.01	-.12						
U	3.43	.04	.04						
Tol		.98	.98						
VIF		1.03	1.03						
Step 2: *F*(4, 337) = 2.72, *p* = .03, R^2 = .031, ΔR^2 = .001, *p* = .79									
b	2.58	.03	-.04	-.003	.06				
SE	.52	.01	.04	.01	.09				
β		.16	-.05	-.02	.04				
t	4.96*	2.87*	-.97	-.36	.65				
L	1.56	.01	-.12	-.02	-.12				
U	3.61	.04	.04	.01	.24				
Tol		.95	.96	.89	.90				
VIF		1.06	1.04	1.13	1.11				
Step 3: *F*(6, 335) = 2.67, *p* = .02 , R^2 = .046, ΔR^2 = .014, *p* = .08									
b	1.47	.03	-.03	-.002	.05	.12	.26		
SE	.85	.01	.04	.01	.09	.13	.12		
β		.17	-.04	-.01	.03	.05	.14		
t	1.73	3.07*	-.78	-.18	.58	.87	2.24*		
L	-.20	.01	-.11	-.02	-.13	-.14	.03		
U	3.13	.05	.05	.02	.23	.37	.50		
Tol		.91	.95	.88	.87	.74	.79		
VIF		1.10	1.06	1.13	1.15	1.36	1.27		
Step 4: *F*(8, 333) = 2.12, *p* = .03, R^2 = .048, ΔR^2 = .003, *p* = .61									
b	4.64	.03	-.03	-.002	-.73	-.63	.01	.18	.06
SE	3.88	.01	.04	.01	.94	.77	.76	.18	.18
β		.17	-.05	-.01	-.45	-.30	.004	.59	.15
t	1.20	3.03*	-.83	-.23	-.78	-.82	.01	.98	.34
L	-3.00	.01	-.11	-.02	-2.57	-2.14	-1.50	-.19	-.30
U	12.27	.05	.05	.02	1.11	.89	1.51	.55	.42
Tol		.89	.94	.88	.01	.02	.02	.01	.01
VIF		1.13	1.06	1.14	119.87	45.95	53.36	125.02	70.66

Note. SE = standard error. Tol = Tolerance. VIF = Variance Inflation Factor. * $p < .05$. L = lower bound of 95% confidence interval for b. U = upper bound of 95% confidence interval for b. Edu = Education. W. Mem = working memory. Mot = motivation. Extra = extraversion. Neu = neuroticism.

Table D7

Moderated Multiple Regression Results for the Certainty Effect

	Constant	Age	Edu	W. Mem	Mot	Extra	Neu	Extra x Mot	Neu x Mot
Step 1: $F(2, 341) = 0.61$, $p = .54$, $R^2 = .004$									
b	1.52	-.01	.003						
SE	.31	.01	.04						
β		-.06	.01						
t	4.85*	-1.07	.09						
L	.91	-.02	-.07						
U	2.14	.01	.07						
Tol		.97	.97						
VIF		1.03	1.03						
Step 2: $F(4, 339) = 0.45$, $p = .77$, $R^2 = .01$, $\Delta R^2 = .002$, $p = .75$									
b	1.74	-.01	.01	-.01	-.02				
SE	.46	.01	.04	.01	.08				
β		-.07	.01	-.04	-.01				
t	3.80*	-1.18	.17	-.63	-.25				
L	.84	-.03	-.06	-.02	-.17				
U	2.64	.01	.08	.01	.14				
Tol		.95	.96	.89	.90				
VIF		1.06	1.04	1.12	1.11				
Step 3: $F(6, 337) = 0.49$, $p = .81$, $R^2 = .01$, $\Delta R^2 = .003$, $p = .56$									
b	2.17	-.01	.003	-.01	-.02	-.04	-.11		
SE	.76	.01	.04	.01	.08	.12	.11		
β		-.07	.01	-.04	-.01	-.02	-.07		
t	2.86*	-1.25	.09	-.70	-.25	-.31	-1.06		
L	.68	-.03	-.07	-.02	-.18	-.27	-.32		
U	3.66	.01	.07	.01	.14	.19	.10		
Tol		.91	.94	.88	.87	.75	.79		
VIF		1.10	1.06	1.13	1.15	1.34	1.27		
Step 4: $F(8, 335) = .37$, $p = .94$, $R^2 = .01$, $\Delta R^2 < .001$, $p = .98$									
b	2.30	-.01	.004	-.01	-.05	-.01	-.22	-.01	.03
SE	3.37	.01	.04	.01	.81	.67	.67	.16	.16
β		-.07	.01	-.04	-.04	-.01	-.13	-.03	.07
t	.68	-1.21	.10	-.71	-.06	-.02	-.32	-.04	.16
L	-4.32	-.03	-.07	-.02	-1.65	-1.32	-1.53	-.33	-.29
U	8.92	.01	.07	.01	1.55	1.30	1.10	.31	.34
Tol		.89	.94	.88	.01	.02	.02	.01	.02
VIF		1.13	1.07	1.13	118.43	42.84	51.18	119.36	68.71

Note. SE = standard error. Tol = Tolerance. VIF = Variance Inflation Factor. * $p < .05$. L = lower bound of 95% confidence interval for b. U = upper bound of 95% confidence interval for b. Edu = Education. W. Mem = working memory. Mot = motivation. Extra = extraversion. Neu = neuroticism.
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