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WHO MAKES BETTER DECISIONS? THE RELATIVE IMPORTANCE OF NUMERACY AND COGNITIVE ABILITIES FOR ELEMENTS OF DECISION MAKING

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WHO MAKES BETTER DECISIONS? THE RELATIVE IMPORTANCE OF NUMERACY AND COGNITIVE ABILITIES FOR ELEMENTS OF DECISION MAKING

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Abstract

The rapidly changing nature of work has increased the importance of non-routine thinking skills required to make decisions under risk and uncertainty. Cognitive ability tests are traditionally considered a robust tool for personnel selection and placement, provided how they assess thinking skills that generalize across many jobs. Tests are often designed to measure general cognitive ability, which is conceptualized as the foundation of higher-order thinking skills. However, other studies have suggested that tests of specific abilities are useful as well. There is growing evidence that numeracy, defined as the ability to apply mathematics in practice, is a strong predictor of decision-making skills. However, much remains to be examined in terms of numeracy's usefulness as a predictor relative to commonly used cognitive ability tests. In this dissertation, I review decision-making competence as a multidimensional performance criterion, in which each of its dimensions have implications for workplace decisions. Using a sample of 355 undergraduate students who completed a battery of assessments, I estimated the relative importance of crystallized ability, fluid ability, and statistical numeracy for predicting overall decision-making competence and the dimensions that comprise it. This study builds on previous incremental validation studies by adopting dominance analysis to partition criterion variance. Numeracy was consistently a superior predictor over fluid ability, whereas the relative importance of numeracy and crystallized ability varied across dimensions. These results contribute to a growing literature on statistical numeracy as an important part of decision-making that is underrepresented in traditional cognitive ability tests. Implications are discussed with respect to the importance of leveraging numeracy in personnel selection and training systems for jobs that require decision-making competence.

Introduction

Economic development often depends on people's ability to comprehend risks and make informed decisions. As the economy continues to grow in complexity, the skills necessary for dealing with risk and uncertainty will become increasingly important (Griffin et al., 2012). Workers now assume more responsibility for managing their roles, and fewer organizations offer well-defined career progressions or guarantee health or retirement benefits (Zaber, Karoly, & Whipkey, 2019). Information technology has transformed how people obtain and share knowledge, increasing the importance of complex skills for integrating information and solving problems (Autor et al., 2003; Frey & Osborne, 2017). Results from large-scale international assessments have prompted concern about people who seem unprepared for roles in the changing economy (Tout et al., 2017). The workplace is becoming polarized, such that lower-skilled workers are increasingly vulnerable to unemployment. These trends have captured the attention of policymakers and raised concerns about the effectiveness of educational and vocational training institutions (Redmer & Dannath, 2019). Results from large-scale international assessments suggest that many adults lack basic literacy and numeracy skills, let alone the more complex skills necessary for adapting to the modern workplace.

Numeracy, in particular, has gained attention as an essential skill for making sense of quantitative information in an increasingly data-driven and technological world (Grotlüschen et al., 2019). Contrary to the abstract mathematics taught in school curriculums, numeracy often refers to practical applications of mathematics in real-world contexts (Geiger et al., 2015). Policymakers have cited innumeracy as a risk factor for unemployment and advocated for resources devoted to workplace numeracy training for adults (Tout et al., 2017). However, determining how to improve numeracy skills as they are practiced on the job can be challenging.

Job analyses have demonstrated that the use of numeracy is not always identified as such (Black et al., 2015). Dealing with quantitative information is deeply embedded in technology or tasks. Some workers refute that they are applying numeracy skills when making decisions, and may instead insist that it is “common sense” (Keogh et al., 2014). However, given the current state of the literature, identifying training needs will likely require a more detailed account of the linkages between numeracy skills and workplace practices.

Recent advances in the study of judgment and decision making offer a potential avenue for addressing the “invisibility” of numeracy in the workplace. A growing body of research has identified numeracy, or more specifically a subset of skills associated with *statistical numeracy* (e.g., practical probabilistic and inductive reasoning skills), as a proxy of general decision-making skill (Cokely et al., 2018). Provided that decisions are made under risk and uncertainty (e.g., one cannot logically deduce a certain solution), there are advantages to being able to evaluate outcomes in terms of magnitudes, distributions, contingencies, and likelihoods. Although it is well-known that people systematically deviate from normative standards for optimal decision-making, there remain individual differences in the ability to do so (Stanovich et al., 2016). Moreover, assessments of decision-making skills have been shown to predict meaningful life outcomes (Bruine de Bruin et al., 2007). To the extent that numeracy reflects the ability to make good decisions in general, there is precedent for linking it to more complex skills and competencies demanded in the modern workplace. This may suggest valuable and currently neglected opportunities for pre-employment testing and needs analysis.

However, there already exists well-established practices for using tests to predict workplace outcomes. Even if numeracy tests are strong predictors of decision-making quality, they may be redundant with existing assessments used in generalized contexts (Blacksmith et al., 2019; Schmidt & Hunter, 1998). Traditionally, decision-making skills have been attributed to cognitive ability, which has been defined many ways, such as the ability to learn and make sense of complex information (Hunt, 2010; Neisser et al., 1996). Theories suggest that people with higher cognitive ability are capable of processing larger amounts of information more efficiently, which is reflected in higher levels of professional competence, such as numeracy and decision-making skills. Over a century of research has shown that performance on cognitive tasks is often correlated, reflecting a common factor (Jensen, 1998; Spearman, 1904). However, decision making is inherently multidimensional, indicating that different cognitive processes may be involved across different types of decisions (Ceschi et al., 2019; Teovanović et al., 2015). This also aligns with calls for research on specific abilities within the scope of general cognitive ability (Scherbaum et al., 2012).

The extent to which numeracy, in a sample of young adults, predicts normative decision-making uniquely from commonly used tests of cognitive ability may justify related applications for industrial and organizational (I/O) psychologists seeking to improve the quality of decisions in organizations. The purpose of this dissertation is to test whether individual differences in statistical numeracy offer unique criterion-related validity for normative decision making tasks, beyond that of other cognitive abilities, in a sample of young educated adults who are preparing for a diverse range of professional careers in science, business, engineering, etc. In the present study, normatively superior decision making is operationalized as a multidimensional performance construct measured by the Adult Decision-Making Competence (A-DMC) scales (Bruine de Bruin et al., 2007). Building on previous studies demonstrating incremental validity of numeracy over individual tests of cognitive ability (e.g., Del Missier et al., 2012; Peters et al., 2006), the present study compared numeracy to cognitive abilities: specifically, crystallized and fluid ability. Dominance analysis was used to evaluate the relative contributions of each construct to explained variance in the criterion (Nimon & Oswald, 2013). Competing hypotheses tested the relative importance of numeracy for predicting overall decision-making and the extent to which its importance varies across dimensions of decision-making competence. To the extent that numeracy predicts decision-making uniquely from cognitive ability, there may be considerable opportunities for using numeracy tests in personnel selection and placement for jobs that require these general decision-making skills.

Numeracy in the Workplace

The importance of mathematical reasoning has long been acknowledged as an important factor for desirable outcomes in work and life (Paulos, 1988). Since the earliest humans started using numbers to count, mathematics has developed into a driving force behind human innovation (Dantzig & Mazur, 2007; Everett, 2019). While mathematics remains the foundation for science, engineering, and technology, there remains the question of its usefulness in domains that are less frequently associated with explicit quantities. Policymakers' interest in mathematics for the workplace can be traced to the "Crowther Report" on education in 1959. The United Kingdom's Ministry of Education (1959) coined the word "numeracy," which was used to distinguish applied mathematics from the abstract mathematics performed in classrooms. Numeracy is sometimes referred to as "quantitative literacy" or "mathematical literacy." The Organization for Cooperation and Economic Development defines numeracy as "ability to access, use, interpret and communicate mathematical information and ideas in order to engage in and manage the mathematical demands of a range of situations in adult life," (OECD, 2013). Precise definitions vary between reports. Generally, numeracy encompasses the skills for using mathematics in real-world contexts.

Numeracy has been incorporated into large-scale assessments used for evaluating education and vocational training institutions across nations (Tout et al., 2017). Many people have deficits in numeracy, including highly-educated professionals (Paulos, 1988; Schwartz et al., 1997). According to the standards on the OECD's Programme for the International Assessment of Adult Competencies (PIAAC), one in five adults have poor numeracy skills. The National Adult Literacy Survey (NALS) indicated that almost half of the U.S. population struggles with simple tasks like calculating discounted prices (Kirsch et al., 1993). Similar studies have also been conducted on children with similar results (PISA, 2019). These findings inspired streams of research on numeracy as it relates to economic outcomes, with the assumption that numeracy skills are directly related to job productivity (Black et al., 2015; Keogh et al., 2014). Research on numeracy practices in the workplace has shed some light on these relationships, but the tacit nature of many contemporary job skills makes it difficult to draw one-to-one linkages between numeracy and work performance.

A growing body of research has shown that numeracy is a robust predictor of decision-making performance (Cokely et al., 2018; Reyna et al., 2009). Many numeracy tests with emphasis on probability and ratios have been developed for the purpose of predicting the ability to interpret and understand risk (e.g., risk literacy) and general decision-making quality. Early research demonstrated that numeracy tends to be important for comprehending medical risks (Lipkus, Samsa, & Rimer, 2001; Schwartz, Woloshin, Black, & Welch, 1997), and has since generalized to other naturalistic domains (e.g., finance, safety; Grounds & Joslyn, 2018; Lusardi, 2012). Recently, attempts at eliciting mechanisms underlying the relationship between numeracy and decision-making have identified strong effects on performance across many decision-making tasks, even after controlling for tests of cognitive ability (Cokely et al. 2012; 2018; Ghazal et al., 2014; Peters et al., 2006; Reyna & Brainerd, 2008).

In the past decade, a handful of narrative reviews of the relationship between numeracy and decision making have been published (Cokely et al., 2018; Garcia-Retamero et al., 2019; Peters, 2012; Reyna et al., 2009), including integrative reviews and theoretical accounts of the cognitive processes underlying numeracy-decision-making relationships. That numeracy sometimes has incremental validity over cognitive ability indicates that performance on decision-making tasks may involve individual differences beyond basic information-processing capabilities (e.g., Liberali et al., 2012; Peters et al., 2006). Most notably, these theories propose that numeracy's predictive power not only follows from differences in logical mathematical processes (e.g., comprehending numerical information or calculating expected values). Rather, many causal explanations for numeracy effects have emphasized the role of factors such as the intuitive recognition of relevant quantities, more precise psychophysical mapping between affective and numerical responses, and more personalized metacognitive knowledge and strategies for contextualizing a decision problem (Ghazal et al., 2014; Peters & Bjalkebring, 2015). That is, the cognitive skills involved in statistical numeracy are expected to transfer to a broad range of decision environments.

Skilled decision theory provides a theoretical account of the primary cognitive mechanisms that generally give rise to superior decision making in experts and non-experts (Cokely et al., 2018). Accordingly, general decision-making skill and risk literacy are distinguished from expert decision-making, which is specific to a domain of expertise. General decision-making skill, as reflected by correlations among decision-making tasks, is said to primarily reflect differences in (1) skilled use of deliberative heuristics (e.g., adaptive strategies used to explore, interpret, and evaluate relevant information) and (2) representative understanding (e.g., highly contextualized and integrated understanding of how the decision problem relates to one's own values, resources, and responsibilities). Traditionally, these conditions have been conflated with complexity in general, in which cognitive ability is thought to enable quick and efficient processing of information (e.g., cold, logical calculation). According to skilled decision theory, however, numeracy skills may tend to be associated with superior decision making via the use of adaptive strategies like "early selection" cognitive control, that allow a decision-maker to overcome processing limitations by pre-emptively narrowing the decision space in alignment with personal goals and values, and thus circumventing capacity limitations of cognitive ability and memory (Cokely et al., 2018). Data from direct tests of these explanations are scarce, and much remains to be learned about how to evaluate decision-making as a criterion.

To date, there are few papers that connect numeracy to workplace decision making. Prior to understanding how numeracy influences decisions, it is necessary to specify what makes a good decision and the relevant contexts.

Decision Quality

Research on decision quality as a performance criterion remains a neglected topic in I/O psychology (Dalal et al., 2010; Zhang & Highhouse, 2018). Instead, studies of organizational behavior tend to emphasize work performance as the "ultimate criterion" with which to evaluate the importance of other variables (Campbell & Wiernik, 2015). Performance is a multidimensional construct including dimensions such as productivity, rule compliance, and helping behaviors. Many performance taxonomies exist, yet few explicitly highlight decision quality as an outcome. Indeed, some frameworks imply the importance of decision criteria, particularly those highlighting adaptability and planning (Griffin et al., 2007). Decision-making, or the choice of a course of action based on judgments of values, preferences, and other situational factors, can be thought of as a precursor to many kinds of performance in the workplace. After all, one must decide to perform. Decision quality also has implications beyond immediate performance, such as its role in safety behavior and setting organizational goals. Effective decision-making is essential for achieving desirable outcomes in organizations.

Evaluating decisions can be done with respect to the quality of outcomes or processes. Yates (1990) defines a successful decision as one that produces an outcome at least as satisfying as that which would have been obtained had one chosen a different option. However, uncertainty makes it impossible to perfectly evaluate the quality of a decision. For example, a Poker player might lose a hand due to being unlucky, despite playing in a way that ought to have produced the highest likelihood of winning given the circumstances. For this reason, much of the research on judgment and decision-making refers to standards for the best processes. Leading standards are grounded in Bayesian probability and expected utility theory, which are arguably the best tools available for formally dealing with risk and uncertainty (Edwards, 1954; Savage, 1972).

Hundreds of studies have shown how decision-makers adopt heuristics and biases that systematically deviate from normative standards (Kahneman, 2003; Tversky & Kahneman, 1974). One of the central tenants of decision theory is that it is rational for people to make decisions in their own best interest (e.g., in accord with well-formed stable, ordered preferences). However, the world is simply too complex to always calculate an optimal response. A limited capacity for processing information requires simpler representations of events, which might lack necessary considerations or be too simplistic overall (Simon, 1947). Much of the earlier research on decision-making has involved cataloging the ways in which people deviate from normative standards and the cognitive processes involved.

Part of the challenge is that decision-making is inherently multidimensional and involves multiple cognitive processes (Yates & Tschirhart, 2006). Not all decision-making contexts are the same, meaning that situations might call for different modes of processing. According to dual-process theories of decision-making, decision quality is a function of the tradeoff between automated and controlled modes of thinking (Kahneman, 2013). Automated processes are fast and intuitive, whereas controlled processes are slow and analytical. The earliest forms of dual-process theories, named default-interventionist theories, propose that decision quality stems from individuals' ability to override intuitions with analytical processing (Frederick, 2005). More recent models have acknowledged that intuitive processes can sometimes result in superior decisions (Bago & De Neys, 2020; Kahneman & Klein, 2009).

To date, one of the most comprehensive dual-process frameworks of human decision-making is Stanovich West, and Toplak's (2016) tripartite model of rationality. Stanovich et al. (2016) proposed an "algorithmic" process that operates between pure intuition and reflection. According to this framework, decision tasks can be characterized by their degree of process-dependence and knowledge-dependence. When prompted with a decision, the effectiveness of the decision-maker's intuitive response is a function of their knowledge and its suitability for dealing with the decision. If the intuitive response is not sufficient, the decision-maker must (1) detect that an override is necessary and (2) carry out the override. In this case, the decision-maker might algorithmically employ a learned strategy. Provided that a strategy is not readily available, dependence on information processing is at its highest. The decision-maker must allocate substantial effort toward reflecting on the appropriate response. This introduces many ways in which individuals can differ in their ability to make good decisions.

Decision-Making Competence

Similar to Stanovich and West's (1999) conceptualization of a general decision-making skill (i.e., rationality), Parker and Fischhoff (2005) developed a battery of tests explicitly for measuring decision-making competence relevant for real-world applications. Rather than pulling tasks directly from previous laboratory studies, Parker and Fischhoff (2005) drew on standards for psychological assessment, such as using multiple indicators to measure a single construct (AERA et al., 2014). Bruine de Bruin et al. (2007) improved the original test, resulting in the Adult Decision-Making Competence (A-DMC) scales. In terms of published construct validation evidence, this is the most well-developed measure of general decision-making skill. It is more reliable than other batteries of heuristics and biases and correlates with some real-world outcomes (Parker et al., 2017). Although a single factor accounts for 25% to 30% of the variance in scores on heuristics and biases as measured by the A-DMC (Bruine de Bruin et al., 2007; Parker & Fischhoff, 2005), correlations between individual tasks are reported as low as .12. The following section breaks down each of the A-DMC scales from a workplace perspective.

Resistance to Framing

Whether communicating or receiving information, the context in which it occurs highlights different aspects of the content without changing the underlying message. The framing effect is the empirical observation that people systematically respond differently to otherwise equivalent information framed in different ways. Sometimes people use framing as a tactic for guiding decisions, like intentionally choosing discourse that promotes a particular vision of organizational culture (Werner & Cornelissen, 2014). Other times, framing can occur in less obvious ways. In a laboratory study, Beck et al., (2017) found that subtle cues related to improving efficiency encouraged people to use shortcut behaviors with additional risks.

There are varying degrees of framing effects, ranging from loose to strict definitions (Keren, 2011; Kuhberger, 2017). Toward the “looser” end, the part of the information that makes it equivalent across different linguistic representations is left ambiguous. Druckman (2001) distinguished between framing in mind and communication. Framing in mind refers to the mental representations that influence the interpretation of information, such as the case of political ideology. Framing in communication refers instead to varying linguistic representations of the same information. A message could be framed in terms of emphasis, in which particular aspects of the message are highlighted over others. It could also be framed in terms of logical equivalence, which is the “strict” definition. This refers to frames that differ in description, but are logically equivalent, as defined by mathematics, for example.

Most empirical research is based on the “strict” definition of framing, in which the framing effect is operationalized as the difference in people’s average responses between two or more frames of logically equivalent information. Of these, a majority of studies manipulate framing on the basis of valence, i.e., framing information positively or negatively. Hundreds of studies have examined the framing effect and its many variations (Kuhberger et al., 1998; Steiger & Kuhberger, 2018). Framing has been investigated in laboratory settings as well as situations in which decisions had real-world stakes (Kuhberger, 2002). The common finding that individuals’ responses systematically differ between frames is often taken as evidence for human irrationality (Kahneman, 2000). According to normative theory, responses to equivalent frames ought not differ on the account of irrelevant information. It is worth noting that no pair of frames can ever be considered truly equivalent in terms of the information they communicate (Sher & McKenzie, 2011). Even logically equivalent frames may carry tacit implications that are detected by the recipient. Due to the challenge of effectively defining a complex concept such as framing, researchers have relied on typologies to understand the phenomena. Perhaps the most comprehensive of these was by Levin et al. (1998), who distinguished risky-choice, attribute, and goal framing.

Risky choice framing

Aside from earlier literature on communication, nearly all of the research on framing and decision making is influenced by Amos Tversky and Daniel Kahneman's work in the late 1900s. They established the dominant paradigm for understanding decision making under risk, in which framing exemplifies the malleability of human decision making. Risky choice framing is a scenario in which the decision-maker chooses between two options: one option offers a certain or "sure-thing" outcome, whereas the other offers the probability of an outcome. The latter is the risky option. Each pair of options can be framed either positively or negatively. A quintessential example of risky choice framing is Tversky and Kahneman's (1981) Asian Disease Problem, which consists of the following prompt:

> *Imagine that the U.S. is preparing for the outbreak of an unusual Asian disease, which is expected to kill 600 people. Two alternative programs to combat the disease have been proposed. Assume that the exact scientific estimate of the consequences of the programs are as follows:*

Participants were randomly assigned to one of two conditions, each with a different pair of options. Those presented with the positive frame chose between options A and B:

- *If Program A is adopted, 200 people will be saved.*
- *If Program B is adopted, there is a 1/3 probability that 600 people will be saved, and 2/3 probability that no people will be saved.*

Those presented with the negative frame chose between options C and D:

- *If Program C is adopted 400 people will die.*

- *If Program D is adopted there is a 1/3 probability that nobody will die, and 2/3 probability that 600 people will die.*

The options are logically equivalent in both conditions. A 1 out of 3 probability of 600 people either surviving or dying corresponds to an expected value of .33 × 600 = 400 people. When presented with the positive frame, 72% chose the Program A, whereas 22% chose the certain option when framed negatively. Under the risky choice paradigm, people have been shown to be systematically risk averse in the domain of losses and risk seeking in the domain of gains. The most dominant explanation of the framing effect is drawn from this finding.

Prior to publishing the Asian Disease Problem, Kahneman and Tversky (1971; 1974) conducted similar studies with gambling tasks. In these earlier studies, risky choices were also framed in terms of gains and losses, but were strictly gambles without narrative explanations, and sometimes involved more than one probabilistic option. Moreover, participants responded to a collection of choice tasks, many of which were intentionally non-equivalent. This was some of the earliest research that formally described how people deviate from expected utility theory. Expected utility theory (Bernoulli, 1954) proposes that individuals calculate the expected values of alternatives under risk. Kahneman and Tversky (1979) specified prospect theory as the successor to expected utility theory. It re-specified the utility function to be nonlinear, such that utility is convex in the domain of gains and concave in the domain of losses. This explains the finding that people often select a gamble with lower expected value when it is framed as a loss.

In the decades since the original formulation of prospect theory, the framing effect has replicated under many conditions (Kuhberger, 1998). However, there are many variations in observations in risky choice. One important distinction is between choice reversal and choice shift. The former is when the majority response between a pair of options reverses as a function of the frame, as was the case with Kahneman and Tversky's (1981) original finding. Choice reversal implies both risk aversion for gains and risk-seeking for losses. Later research found that bidirectional effects sometimes do not replicate (Kuhberger, 1998). Rather, choices shift, such that a framing effect is present for one condition, but not the other. For example, losses might loom larger while the difference certain vs. risky choice is negligible for gains.

Attribute framing

Levin et al. (1998) proposed that attribute framing is the "purest" form of the framing effect. It offers perhaps the greatest insight into the influence of descriptive valence because of its sheer simplicity. Attribute framing involves reframing aspects of the same information either a positive or negative light, after which the recipient makes an evaluation, usually scored with a Likert scale. In the earliest example of attribute framing, Levin and Gaeth (1988) found that perceptions of the quality of ground beef were influenced by whether it was labeled as 75% lean or 25% fat, which correspond to positive and negative frames, respectively. In addition to being simpler, attribute framing is perhaps the most representative of tasks encountered in the real world. Many people build careers as marketers and advertisers figuring out the most effective frames for influencing consumer decisions.

Many accounts have been proposed to explain the attribute framing effect, all of which share a similar theme. Levin et al. (1998) suggested that information processing is at the root, in that positive and negative labels elicit favorable and unfavorable associations in memory, respectively. This explanation, applicable to valence frames of all sorts, subsumes prospect theory, which is specific to decisions under risk. Framing a choice in terms of gains or losses is sometimes considered analogous to framing it positively or negatively (e.g., Peters & Levin, 2008). In attribute framing, the effect is almost always described in terms of a choice shift, as opposed to the choice reversal sometimes observed in risky choice.

Research has identified a number of boundary conditions for each of the different types of framing effects. People are sensitive to changes in language, which can be modified to moderate the size of framing effects. Mandel (2014) conducted a series of experiments in which the Asian Disease Problem frames were manipulated to be “exact,” (i.e., “exactly 200 people will be saved”) or qualified with “at least” (i.e., “at least 200 people will be saved”). Framing effects disappear in the former case, but are apparent in the latter, suggesting that framing can be attributed to how people represent magnitude by default. Mandel (2014) argued that framing bias is evidence for human irrationality rests on the assumption that numbers used to represent expected values of options are interpreted as exact values.

Indeed, a large part of the framing effect is attributed to how individuals make sense of the numbers. Multiple studies have found that people with higher numeracy exhibit smaller framing effects (Peters et al., 2006; Peters & Levin, 2008). Similar explanations have been offered for attribute and risky choice framing, in which highly numerate people are thought to transform framed magnitudes into their normative equivalents (Peters, 2012) and by being more likely to draw meaning from number comparisons in judgments (Peters et al., 2006). Less numerate people, on the other hand, appear to integrate fewer pieces of information and are more heavily influenced by non-numeric information sources, such as mood. Likewise, cognitive ability is thought to suppress the framing effect for similar reasons (Simon et al., 2004; Stanovich & West, 1998). People with a higher capacity for processing information are more likely to reflect on the task and draw normative conclusions (cf. Corbin et al., 2010).

Recognizing Social Norms

When making decisions, people often attempt to integrate the many viewpoints of others affected by the decision (Mumford et al., 2008). Organizations develop cultures and routines that determine the acceptable criteria for everyday decisions. Social norms, defined as shared perceptions of how one should behave and make decisions, are important criteria for social environments. Some definitions of decision quality emphasize the role of accountability, such that a "good" decision is one perceived by others to have considered the appropriate cues and maintain consistency with processes that were determined by the group (Lerner & Tetlock, 1999). Social norms are discussed frequently in the study of occupational health and safety (Fugas et al., 2011; Hammer et al., 2004). Perceived social norms can determine when someone decides to follow a procedure as it is written, or take shortcut behaviors that save time while increasing risk of injury. Making decisions that correspond to social norms requires assessing them accurately. Productivity is determined in part by how quickly and effectively newcomers can identify these norms and socialize into new organizations (Chao et al., 1994).

Under/Overconfidence

People often believe they are more competent, intelligent, and rational than reality suggests. Such overconfidence is often attributed as the cause of many decision-making errors, including highly influential disasters such as the British Petroleum Deepwater Horizon explosion in 2010 (Sylves & Comfort, 2012). Daniel Kahneman (2013), who won the Nobel Memorial Prize in Economics for his research on thinking errors, quipped that overconfidence (specifically, optimism bias) is the most significant error of them all. People who are overconfident might take on projects that are beyond their abilities, allocate less effort toward learning, or mislead coworkers toward believing outcomes are guaranteed when the reality is uncertain (Meikle et al., 2016; Vancouver & Kendall, 2006). Likewise, under-confidence can lead to maladjustment in the workplace, leading one to miss out on opportunities or exhibit indecisiveness at critical stages during a project (Potworowski, 2010). Although confidence itself can be an important and positive influence on motivation and interpersonal relationships, it is the proper calibration of confidence regarding one's judgments that is a critical decision-making skill.

Overconfidence can manifest itself in a variety of ways. Moore and Healy (2008) classified three ways in which confidence is over/under-estimation, over/under-placement, and over/under-precision. Overestimation refers to inflated perceptions of one's ability, how well they are performing, and the likelihood of achieving outcomes. This is related to optimism bias, which is often attributed to projects that fail to meet expectations (Lovallo & Kahneman, 2003). Overplacement is when one perceives themselves to be more competent or likely to achieve an outcome relative to others, as illustrated by the "better-than-average" effect, which describes how people perceive themselves to be better decision-makers than others (Pronin et al., 2002). Lastly, overprecision refers to being more certain about beliefs than is warranted by the available information.

Some people are better at calibrating their judgments than others. Kruger and Dunning (1999) coined the "unskilled and unaware" phenomenon, in which the people lower competence are the most overconfident in terms of calibration. On the contrary, those who are the most competent tend to be well-calibrated, if not slightly underconfident in their abilities. People with higher cognitive ability are more likely to acquire knowledge and skill at a faster rate (Ackerman, 1988). Following this reasoning, workers with higher cognitive ability are expected to be more accurate in their self-judgments on account of being more skilled. However, cognitive ability is not always a useful proxy of acquired knowledge and skill. Studies that directly compared ability test scores to judgment calibration found a negligible relationship between them (West et al., 2012).

Skilled decision theory proposes that numeracy reflects a level of metacognitive savvy, in which people are more likely to deliberate and calibrate their judgments (Cokely et al., 2018). Ghazal et al., (2014) reported data a large sample of highly educated people who evaluated their confidence in their judgments on a handful of paradigmatic decision-making tasks. In both samples, relationship between numeracy and confidence judgments of accuracy was curvilinear, indicating those with the highest and lowest numeracy were more calibrated in judging their accuracy. The correlation between judgmental accuracy and confidence was moderated by numeracy, such that those with higher numeracy were better calibrated.

Applying Decision Rules

When making choices among options with multiple criteria, there are normative standards for choosing options with the optimal value across all the attributes. The field of operations management is devoted to applying computer models for optimally solving organizational problems (Tillman & Cassone, 2012). For example, one might rely on a tool to optimize the trade-off between the quality of a production line and the time required to produce a set quantity. On the other hand, people left to their own devices tend to rely on simple rules that enable them to make decisions more quickly, especially under constraints such as time pressure. Although these strategies reduce effort, they can produce suboptimal results. Payne et al. (1993) provide many examples of decision rules, some of which were used for the development of the A-DMC. The “equal weights” rule involves choosing the option with the overall highest quality across all of its attributes. The “elimination by aspects” rule involves selecting the option that meets a minimum threshold for the most important attribute. When two options share the same value of the most important attribute, the same rule is applied to the next attribute, and so on until one option’s attribute has a higher value than the other.

One notable example of applying decision rules in organizations is deciding how to decide. In the 2015 letter to Amazon.com shareholders, Jeff Bezos described some of the company's heuristics for making decisions in a fast-paced, competitive environment. Always deliberating on decisions and waiting until one has acquired enough information to make the rational choice can be slow, costly, and ineffective. One way to decide whether to invest additional effort into a decision is by classifying it as a "one-door" or "two-door" decision. One-door decisions are irreversible, consequential, and thus require careful consideration. In contrast, two-door decisions are reversible, have short-lived consequences, and can be reconsidered later on. By making this distinction, Amazon's board attempts to maintain the adaptability of a startup despite being one of the world's largest employers.

Among normatively superior decision-makers, one possibility is that higher cognitive ability enables faster and more efficient computation of expected values and axiomatic principles. In this case, better decision-makers are less likely to rely on simple strategies. Cokely and Kelley (2009) tested this proposition by collecting think-aloud responses from university students making a series of risky choices in the laboratory. Contrary to the prior suggestion, only a small minority of participants explicitly calculated the optimal response. Indeed, the higher performers deliberated for longer, but the nature of deliberation involved personalized heuristic strategies (e.g., imagining what the payoff would be like) instead of multi-attribute optimization. Cokely and Kelley (2009) proposed that people with higher cognitive ability (or numeracy) are better at narrowing the search space of possible options early in the process of making a choice, which eliminates the need for effortful computation.

Although simple rules are often cited for leading to suboptimal choices, research on real-world decision-making outside of the laboratory has shown that simple rules sometimes out perform more complex ones, even computerized algorithms (Gigerenzer, 2008). This perspective draws from the methods for predicting out-of-sample events beyond the available information, in contrast to traditional statistical modeling, which tries to find the optimal fit to existing data. To date, Cokely and Kelley's (2009) finding is one of the strongest pieces of evidence for skilled decision theory because it provides explicit evidence of individual differences in the cognitive processes involved in risky choice.

Consistency in Risk Perception

Making decisions requires judging the probabilities of events that might occur. Risk perception is a necessary antecedent to the implementation of decisions because one cannot respond to risks that are not recognized. For this reason, risk perceptions are frequently studied in the context of project planning (Zhang et al., 2015). When a decision-maker is able to accurately assess risks (e.g., potential safety concerns), they can anticipate and take precautionary action. Workers who perceive risks to be higher are more likely to engage in safety compliance behaviors (Xia et al., 2017). Many characteristics of the individual and the environment can influence the extent to which actions are perceived as risky. For example, catastrophic risks (e.g., caustic burn) tend to be perceived as more severe than chronic risks (e.g., long-term effects of radiation exposure).

Normative decision theory posits that risk perceptions (i.e., probability judgments) should be consistent with logical rules. Many people have inaccurate or inconsistent perceptions of risk relative to objective reality (Fischhoff et al., 1978). First, risk perceptions must have temporal reliability (i.e., risk of event happening over longer period of time is greater than risk of the event happening in a shorter span of time). Second, risk perceptions must follow principles of set theory (i.e., risk of any event from a set of events is greater than for any subset of that set).

Lastly, elicited probabilities of complementary events (e.g., “A” and “not A”) must sum to 100%.

Resistance to Sunk Cost

One of the tenants of decision theory is that people ought to make decisions based on future outcomes, regardless of what happened in the past. This contrasts with decision-making behavior named the sunk cost effect, in which one decides to follow through with an investment once it loses its value (Arkes & Blumer, 1985; Roth et al., 2015). What is now recognized as sunk cost was originally named the “Concorde fallacy” by Dawkins and Carlisle (1976) after an incident in which British and French governments continued to fund development of the Concorde supersonic jet after it was apparent that doing so was not economically viable. Arkes and Blumer (1985) demonstrated that the phenomenon generalized across many situations. In their experiments, people who spent more on movie tickets attended more shows, opted for a less desirable vacation that cost more, and reported greater willingness to continue prior investments in failing projects.

The sunk cost is thought to appear frequently in the daily operations of organizations. One might find that a project is no longer relevant to an organization’s goals yet follow through with putting time into it since the financial costs were already paid for. The sunk cost effect is a precursor to escalation of commitment, which is when one decides to invest additional resources into an investment that lost its value (Woods, 2015). Although most frequently studied in financial scenarios (in which traders can sink their money into high-risk investments), sunk costs are also studied in the context of project management, in which the time and resources needs to be allocated wisely. Many anecdotal examples of sunk cost have been reported in articles about project management decisions. For example, the City of Denver continued to maintain an automated baggage handling system throughout the 1990s and early 2000s despite failed tests and airlines opting to use their own processes (Shore, 2008). When the system was finally abandoned, stakeholders in the project were still liable for $1.5 billion.

Who Makes Good Decisions?

An important concern for personnel selection and assessment is eliciting the knowledge, skills, abilities, and other characteristics that comprise superior decision making. Although the differential psychology of decision making is rather new, more than a century of research on individual differences offers a starting point for building theoretical foundations. Much of the recent literature has asked whether foundational cognitive abilities are sufficient for explaining individual differences in decision making (Bruine de Bruin et al., 2020; Stanovich, 2009). By examining the statistical organization of test scores, we can make inferences about the abilities underlying those test scores, which provide a measurement of thinking skills relative to others.

A person who generally makes good decisions may be described as “intelligent” or “rational.” Intelligence generally refers to the ability to successfully accomplish one’s goals in a given environment (Mackintosh, 2011). However, despite scholars writing about intelligence for centuries, there is considerable debate about the “best” definition of the construct and about the underlying causes and mechanisms that explain individual differences. For example, some researchers emphasis differences in the mechanisms of intelligence in terms of the neurophysiology responsible for processing information (Jung & Haier, 2007). Intelligence has also been described as “the ability to deal with […] complex information” (Gottfredson, 1997, p. 79) and “the ability to learn” (Schmidt, 2002, p. 188). Boring (1923) went as far to assert that “intelligence is what the tests test,” (p. 23). There appears to be at least a kernel of truth to this last definition: Judgments about one’s intelligence are generally based on their scores on mental tests. Perhaps in part because of these and related debates, many researchers refer to "cognitive ability" instead of "intelligence" when describing the broad domain of thinking skills reflected in these assessments.

Over a century of research has demonstrated that scores on tests involving problem-solving and reasoning are strongly correlated with each other, indicating that an underlying factor may be the common cause of many desirable outcomes in work and life (Jensen, 1998; Spearman, 1904). This factor, when expressed as the first principal component of a factor analysis, is often called "*g*." General mental ability (GMA) is another phrase used to describe the common underlying factor derived from a set of mental tests, without strict requirements on how that factor is derived. For example, a single test might be described as an indicator of GMA. In this view, test scores are solely comprised of variance attributed to GMA and variance specific to the test. Volumes of research have contrasted models in which GMA is a common cause of test scores versus those in which each test (or set of tests) represents a unique ability independent of shared variance with other abilities (Schneider & McGrew, 2012; Thurstone, 1938).

Developments in latent variable modeling allowed for compromises between the different perspectives of cognitive ability (Gustafsson & Balke, 1993). Hierarchical and bifactor models of mental test scores include both general and specific ability factors. To date, perhaps the most comprehensive structure of cognitive abilities is the Cattell-Horn-Carroll (CHC) model (Schneider & McGrew, 2012). This model is an extension of Cattell's (1941) distinction between fluid (Gf) and crystallized ability (Gc), in which cognitive ability tests are distinguished by the extent to which they measure information-processing capabilities versus acculturated knowledge. Carroll (1993) later expanded the model to incorporate over a dozen abilities subordinate to GMA, although fluid and crystallized ability remain the dominant factors.

Fluid ability is defined as the general capacity to solve novel problems, encompassing deductive and inductive reasoning. Descriptions of fluid ability are similar to those of GMA, enough so that some researchers consider them to be the same. Indeed, Gustafsson and colleagues' models demonstrated that fluid ability loads more strongly on GMA than any other abilities (Gustafsson, 1984; Undheim & Gustaffson, 1987). One of the key tenants of fluid ability is that it is considered to be "culture-free." That is, it is thought to capture an information-processing capability that is independent of knowledge. Stanovich (2012) described fluid ability as the "algorithmic" mind that is responsible for decoupling elements of the decision scenario, allowing one to perform mental simulations of potential outcomes. It can also be considered part of the "reflective" mind, which encompasses attention and executive functions. Fluid ability is strongly correlated with tests of attentional and working memory processes.

Carroll's (1993) model partitioned fluid ability into deductive, inductive, and quantitative reasoning factors. Reviewing test items used as indicators of quantitative reasoning, many can be classified as conventional numeracy, which includes foundational arithmetic, algebra, and geometry (Ghazal, 2014). This differs from the aforementioned research that measured statistical numeracy: probabilistic reasoning and mathematical operations (e.g., converting decimals to fractions). Cokely et al. (2018) pointed out that "inductive reasoning" as used to describe fluid ability tests is different from "inductive logic" used to describe decision making under uncertainty. Tests like Raven's Progressive Matrices are considered tests of inductive reasoning, but one can ultimately deduce the single, correct answer.

Crystallized ability reflects broad acculturated knowledge that is acquired in formal education and over the course of a lifetime. Carroll (1993) identified many facets of crystallized ability including verbal reasoning, reading comprehension, spelling, grammar, communication, lexical knowledge, phonetic coding, and cloze abilities (i.e., inferring the missing word in a sentence or paragraph). Decision-making competence may be considered a special case of crystallized ability, reflecting specific knowledge that had been gained through learning and experience. Stanovich (2012) describes crystallized ability as part of the "autonomous" mind, which reflects a set of rules and procedures that individuals are capable of intuitively applying in decision situations. Nevertheless, Stanovich (2012) asserts that crystallized (and fluid) ability tests fail to capture the full range of knowledge structures relevant to decision-making.

To date, Allan (2018) conducted one of the most comprehensive studies of cognitive abilities and decision making. Part of her study was an exploratory factor analysis of test scores from participants who completed five hours of assessments. This analysis revealed that scores on numeracy and decision-making tests loaded together on a single factor that was correlated, but distinct from other cognitive abilities. One reason that numeracy has been repeatedly shown to have incremental validity over cognitive ability is that it represents an important part of the construct domain that is often neglected in commonly used assessments. To the extent that making decisions under risk and uncertainty are unique from the processes tapped by cognitive ability tests, there are opportunities for expanding assessment systems.

Purpose

The present study offers insight into the use of numeracy tests in the workplace by integrating concepts from I/O psychology and judgment and decision making. Studies have repeatedly demonstrated evidence of numeracy as a predictor of normatively superior decision making even after statistically controlling for cognitive ability (Cokely et al., 2018). While the evidence of incremental validity is suggestive, there are several unanswered questions. The purpose of the present study is to provide a direct test of the relative importance of numeracy for decision-making competence, as compared to other cognitive abilities (specifically, crystallized and fluid ability), and to examine the extent to which the relations between numeracy and performance differs across the multiple dimensions of decision-making competence. Drawing on different perspectives of GMA, this dissertation tests competing hypotheses of numeracy as a unique vs. redundant predictor of decision-making. In doing so, it addresses the following research questions:

> Research Question 1: *What is the relative importance of numeracy and cognitive abilities for predicting decision-making competence?*

> Research Question 2: *Does the relative importance of numeracy and cognitive abilities vary across dimensions of decision-making competence?*

When considering a new predictor for workplace applications, best practices involve assessing its validity relative to existing tools (Van Iddekinge & Ployhart, 2008). The use of cognitive ability tests for assessing a broad range of thinking skills across jobs is already well-established in I/O psychology (Dilchert, 2018). Their widespread use is guided by two theoretical principles: (1) that various ability tests measure the same underlying construct of GMA and (2) that the predictive validity of GMA is similar across jobs (Schmidt & Hunter, 1998). The first principle is supported by volumes of research adopting the unidimensional view of GMA as the root cause of performance across various problem-solving tasks (Ree et al., 1994; Ree & Earles, 1991). This means that scores on any cognitive task measure the same "*g*" regardless of domain (i.e., "indifferent to the indicator."). The second principle is that higher GMA is generally advantageous regardless of the job, as demonstrated by it being a robust predictor of job performance (Schmidt & Hunter, 1998).

Given these principles of cognitive ability testing, researchers have raised concern about construct proliferation, defined as the use of multiple terms or measures for the same underlying construct (Shaffer et al., 2016). One of the major contributions of Schmidt and Hunter's (1998) meta-analysis was that it contrasted with previous studies that insisted on developing unique tests for each job. There is little debate that tests of job-relevant knowledge and skill are stronger predictors than cognitive ability in practice (Sackett et al., 2017), but they are less generalizable by definition. For example, numeracy might outperform an ability test for predicting performance in jobs that involve mathematics (e.g., accountant, engineer), but is less likely to be as useful for jobs that do not (e.g., dental hygienist, writer).

Researchers need to make informed decisions about the trade-off between generalizability and specificity in assessment. Conceptually, numeracy is a skill that can be developed, yet numeracy test scores are likely to reflect levels of cognitive ability as well. Indeed, numeracy test scores are correlated with scores on ability tests (e.g., Brooks & Pui, 2010). Theoretically, people with higher cognitive ability are more likely to attain higher levels of knowledge and skill over time, which subsequently results in better performance across tasks (Ackerman, 1988; Hunter, 1986). This investment theory proposes that foundational mental capacities such as fluid ability correspond to limited resources that are invested more or less into cognitive development. If variance in decision-making competence attributable to numeracy is largely shared with cognitive ability, it would be evidence that numeracy tests are redundant with the ability tests already used in many organizations.

From a theoretical perspective, high levels of shared variance would point to the potential value of *g*-theory interpretations of decision making. Blacksmith et al. (2019) adopted a *g*-theory approach to validating the A-DMC by including it within a broader factor analysis of cognitive ability measures. Blacksmith et al. (2019) tested competing models in which decision-making competence was constrained under the common factor model or as distinct, yet correlated with cognitive ability. The latter was a better fit to the data, but the correlation between cognitive ability and decision-making competence was .96 after correcting for measurement error. Note that Blacksmith et al. (2019) included numeracy as an indicator of cognitive ability in their model. Ree and colleagues emphasize the importance of *g* for interpreting results from incremental validation studies (Ree et al., 1994; Ree & Earles, 1991). If numeracy is just one indicator of a broader construct, then its usefulness as a distinct part in assessment batteries is limited. Whatever construct-relevant variance is captured by numeracy tests may be the same as that captured by ability tests already being widely used. Accordingly, and with respect to Research Question 1, I examined the following hypothesis.

Hypothesis 1: *Numeracy is not relatively important for predicting decision-making competence compared to crystallized and fluid ability.*

Many studies have already demonstrated the incremental validity of numeracy over cognitive ability for predicting performance on decision-making tasks (Allan, 2018; Del Missier et al., 2012; Peters et al., 2006). However, these small increments in criterion-related validity might not represent the *relative importance* of numeracy for prediction per se (LeBreton et al., 2007; Nathans et al., 2012). Although numeracy can be encompassed in the measurement structure of broader cognitive abilities, recent studies on the use of specific ability tests suggests they may be underutilized in practice. Lang et al. (2010) demonstrated how shared variance between predictors in incremental validation studies is always attributed to those entered first in the model. GMA can appear to be the most important predictor in incremental validation studies while specific abilities are the strongest single predictors, as demonstrated by relative importance analysis. Using one variation of this approach named dominance analysis, Lang and Kell (2019) showed that each specific ability is a unique predictor of job income whereas hierarchical regression showed negligible incremental validity over GMA.

Previous research has already demonstrated that numeracy has incremental validity over cognitive ability for predicting decision making, indicating that numeracy tests are at least not fully redundant with existing measures (Allan, 2018; Del Missier et al., 2012; Peters et al., 2006). Allan (2018) analyzed a broad array of cognitive abilities and decision-making tasks. Aggregating all the variables, she observed that numeracy and decision-making performance corresponded to a factor distinct from other cognitive abilities (specifically fluid and crystallized ability). Contrary to Blacksmith et al., (2019), Allan (2018) emphasized numeracy as a proxy of decision-making skill underrepresented by traditional ability tests.

Few studies have examined decision-making skills in the workplace (cf. Ceschi, Costantini, et al., 2017; Ceschi, Demerouti, et al., 2017), let alone validated measures of decision-making skills against established workplace criteria. To the extent that numeracy uniquely accounts for variance in decision-making competence beyond cognitive ability, it may serve as a proxy for assessing decision-making in the workplace. Whereas interventions targeted at improving cognitive abilities are largely ineffective (Melby-Lervåg et al., 2016), numeracy deficits can be mitigated using well-designed visual aids and risk communications (Garcia-Retamero & Cokely, 2017). Numeracy tests might serve as useful tools in place of or in combination with cognitive ability tests for identifying individuals and groups at risk of making poor decisions in the realms of work performance, safety, and other organizational behaviors. Numeracy tests require only half the time to administer relative to ability tests like the Wonderlic (Cokely et al., 2012). At the very least, unique variance in the criterion attributable to numeracy would be evidence of its usefulness in selection beyond tests of cognitive ability. Accordingly, and with respect to Research Question 1, I examined the following hypothesis.

> Hypothesis 2: *Numeracy is relatively important for predicting decision-making competence compared to crystallized and fluid ability.*

Just as the multidimensional nature of cognitive abilities needs to be considered for assessment, so does that of the performance criterion (Murphy & Shiarella, 1997). The A-DMC was intended to be multidimensional, although its dimensions were not organized the way in which the authors expected (Bruine de Bruine et al., 2007; Parker & Fischhoff, 2005). Studies of individual differences in decision-making tend to emphasize the shared variance between dimensions, thus modeling decision-making competence as a unidimensional construct. Although the general factor model provides a better fit to the data than alternative measurement models, other evidence for the unidimensionality of decision-making competence is weak. Low correlations between the A-DMC subscales and indicate meaningful differences between the components, even if they share lots in common.

Stanovich et al.'s (2016) framework for organizing the cognitive processes involved in decision making can be used to form expectations of the processes involved in decision-making competence. In their broader assessment of decision-making performance (named the Comprehensive Assessment of Rational Thinking (CART), Stanovich et al. (2016) distinguished between knowledge- and process-dependence. Decision tasks with high knowledge-dependence can be performed quickly and accurately having learned the necessary information (with the exception of cases in which the decision maker one has "contaminated" information, e.g., false beliefs). Decisions with high process-dependence require higher levels of cognitive processing to integrate multiple sources of information and exert control over intuitive errors.

Although Stanovich et al. (2016) did not collect any data on the A-DMC, they described how they would expect the A-DMC scales to align with these dimensions, and made connections to their own assessment when possible (e.g., the CART includes a measure of sunk cost, but not social norms). One apparent feature of this framework is that knowledge- and process-dependence are not mutually exclusive. As part of assessing the relative importance of numeracy and cognitive ability for predicting decision-making competence and its dimensions, the present study will estimate the attributable variance that is either shared or unique to each of the predictors. Dimensions with high knowledge- and process-dependence (e.g., Consistency in Risk Perception) may be expected to be attributable to greater proportions of shared variance than dimensions with high demands along one of the continua.

Fewer studies have examined how the criterion-related validity of cognitive abilities vary across the dimensions of decision-making competence. To understand how decision-making changes with aging, researchers have distinguished between decisions that rely on fluid and crystallized ability (Finucane & Gullion, 2010; Li et al., 2013). Scores on tests of fluid ability tend to peak around the age of 20 years, after which they decline as people get older (Staff et al., 2014). In contrast, crystallized ability tends to increase with age, although the rate can slow with time and potentially reach an asymptote (Beier & Ackerman, 2005). These patterns have been used to explain why older adults tend to perform better on some decision-making tasks and worse on others. For example, Applying Decision Rules can require sustained attention and processing of alternatives, which can become more difficult with age. Crystallized ability can compensate for declines in fluid ability via decision rules retrieved from memory. These differences have implications for choosing which predictors to use in workplace assessment. The multidimensionality of performance criteria has been discussed at length in the literature on assessment in organizations (Edwards, 2001; LeBreton et al., 2007). That performance (and decision making) encompasses a broad range of dimensions is justification for using multiple predictors in assessment, which may be weighted corresponding to assessment goals. It is possible that the proportions of unique and shared variance attributable to numeracy and cognitive ability varies across dimensions of decision-making competence. If so, this would offer insight into differences in cognitive processes involved in decision-making tasks, which could inform ways of optimally predicting decision-making under different weighting schemes.

How the relative importance of numeracy differs across dimensions of decision-making competence provides insight into the generalizability of numeracy tests. Many conventional tests of decision-making, including some of those in the A-DMC, explicitly rely on quantitative reasoning. For example, resistance to framing involves basic transformation of numbers, such as realizing that losing 20% is the same as keeping 80%. To this extent, transfer of identical elements is expected, and often considered for jobs where direct assessment of knowledge and skills are recommended. One of the assertions of skilled decision theory is that numeracy encompasses self-regulatory skills that are relatively unassessed by cognitive ability tests (Cokely et al., 2018). Various studies have begun to elicit the self-regulatory skills tied to numeracy, but rarely distinguish how these are unique from those reflected in cognitive ability (Ashby, 2017; Ghazal et al., 2014). Research Question 2 addresses the generalizability of numeracy for predicting different dimensions of decision-making. Accordingly, and with respect to Research Question 2, I examined the following hypothesis.

> Hypothesis 3: *Numeracy is relatively important for predicting decision-making competence compared to crystallized and fluid ability, but its importance varies across dimensions of decision-making competence.*

Research on aging set a precedent for the relative importance of fluid and crystallized ability to vary across dimensions of decision-making competence (Bruine de Bruin et al., 2014). Whether this variability is consistent within a cross-sectional sample of young adults has yet to be determined. More importantly, it remains unknown how numeracy functions relative to these cognitive abilities. Should numeracy account for a proportion of variance in A-DMC scales that are not explicitly mathematical, it would provide support for recommendations about the utility of numeracy as a predictor of decision quality in performance domains where mathematics does not figure prominently (Cokely et al., 2018).

Method

Participants

Data were collected as part of a larger research effort. The present study aggregated data from two samples: 309 undergraduate (63.7% female) students from the University of Oklahoma (OU) (Allan, 2018) and 46 (28.3% female) undergraduate students from Michigan Technological University (MTU). Both samples were recruited from the subject pools at their corresponding universities. Each participant received credit toward a psychology course for their participation. Both studies involved a sequence of online assessments including tests of numeracy, cognitive ability, and decision making. Scores were aggregated into a total sample of 355 participants. Demographically, the total sample contained 22 (6%) Hispanic, 17 (5%) American Indian or Alaska Native, 33 (9%) Asian, 25 (7%) Black or African American, and 15 (4%) Other.

Measures

***Crystallized ability*.** The Wonderlic Personnel Test (WPT) is a well-established reasoning test designed explicitly for personnel selection (Wonderlic, 2007; Wonderlic & Hovland, 1939). Although the WPT is frequently considered a direct test of GMA, its content (e.g., analogical, logical, mathematical, and verbal reasoning) is representative and more strongly correlated with reading comprehension and acculturated knowledge (Hicks et al., 2015; Matthews & Lassiter, 2007). Participants were allowed 12 minutes to answer 50 items correctly.

Fluid ability. Participants completed Bors and Stokes' (1998) abbreviated version ofRaven's (1936) Advanced Progressive Matrices (APM). The APM is considered among the best measures of fluid ability and one of the most representative tests of GMA (Carroll, 1993;

Gustafsson, 1984). One reason that APM is effective at measuring fluid ability is that it excludes content that would otherwise introduce test score variance attributable to language and acculturated knowledge. The test comprised of 12 items in multiple choice format. Participants were prompted to select one figure from a list of six options that completes a pattern in which one of the pieces is missing. Items were presented in order of increasing difficulty.

Numeracy. The Berlin Numeracy Test-Schwartz (BNT-S) combines three items from Schwartz et al.'s (1997) numeracy test and four items from Cokely, Galesic, Schulz, Ghazal, & Garcia-Retamero's (2012) Berlin Numeracy Test developed for general and highly education populations, respectively. Together, these 7 items allow for discriminability across the full range of numeracy in the general population. Test items cover probability and statistics like judging proportions, comparing fractions, and estimating conditional probabilities. For example:

> *In a forest 20% of mushrooms are red, 50% brown and 30% white. A red mushroom is poisonous with a probability of 20%. A mushroom that is not red is poisonous with a probability of 5%. What is the probability that a poisonous mushroom in the forest is red?*

Decision-making competence. The A-DMC comprises six scales: Resistance to Framing, Recognizing Social Norms, Under/Overconfidence, Applying Decision Rules, Consistency in Risk Perception, and Resistance to Sunk Costs. Bruine de Bruin et al.'s (2007) original validation study included a 7th scale named Path Independence, which was excluded from subsequent research due to poor reliability and validity (e.g., Del Missier et al., 2010). The A-DMC items are publicly available from the Society for Judgment and Decision Making. Total A-DMC scores were calculated as the arithmetic mean of the 6 standardized subscale scores. Reports of the A-DMC’s internal consistency range from .39 to .77 as measured by Cronbach’s alpha. In the following section, internal consistency (α) and test-retest reliability (r_{tt}) coefficients are the values reported by Bruine de Bruin et al. (2007).

Resistance to Framing (α = .62; r_{tt} = .58) is comprised of 14 items that described a situation and prompted participants to judge their relative preference between two options on a scale of 1 (i.e., definitely the first option) to 6 (definitely the second option). Seven of the items were risky choice frames in which participants chose between a certain and risky option that were framed in terms of gains or losses (e.g., the *Asian Disease Problem* described earlier). Seven of the items were attribute frames in which participants evaluated positively and negatively framed versions of the same items (e.g., quality of ground beef described as 80% lean or 20% fat). Sets of positive and negative frames were presented separately, with other A-DMC tasks between them. Scores were calculated as the mean absolute difference between ratings for the positive and negative frames of each item.

Recognizing Social Norms (α = .64; r_{tt} = .46) is comprised of 16 pairs of items corresponding to a set of behaviors (e.g., "*Do you think it is sometimes OK to not be on time for appointments?"*). Participants self-reported whether they engage in each of the behaviors, followed by estimating the proportion of the population they believed do so (e.g., "*Out of 100 people your age, how many would say it is sometimes OK to not be on time for appointments?"*). The normative proportion was specified as the proportion of people in the sample who reported engaging in the behavior. Each participant's score was the rank-order correlation between their estimates of the population proportion and the actual proportions derived from the sample.

Under/Overconfidence (α = .77; r_{tt} = .47) was measured with 34 true or false statements derived from reference guides to a variety of topics (e.g., *"Stress makes it easier to form bad habits,"* "*Self-employed people pay the same amount of taxes as people who work for an employer.*") After specifying whether a statement was true or false, participants rated their confidence in their answer on a scale from 50% (just guessing) to 100% (absolutely sure). Scores were calculated as 1 minus the absolute difference between mean confidence rating and percentage correct, such that higher scores reflect more calibrated performance.

Applying Decision Rules (α = .73; r_{tt} = .77) comprised of 10 items measuring the ability to follow the appropriate rule when choosing among options with multiple features (e.g., elimination by aspects, satisficing, lexicographic, and equal weights rules). For example, participants were told that a hypothetical person is buying a DVD player. There were 5 choices involving DVD players with various features. Scores are the number of correct responses. For example:

		Features				
		Picture Quality	Sound Quality	Programming Options	Reliability of Brand	Price
DVD	A	5	3	5	5	$369
	B	2	5	4	1	$369
	C	4	5	2	3	$369
	D	3	5	3	1	$369
	E	3	5	3	4	$369

Andy wants the DVD player with the highest average rating he can get while still making sure to keep the best rating on Sound Quality.

Which one of the presented DVD players would Andy prefer?

In this example, DVD player A is eliminated because it fails to meet the criterion of best rating on sound quality. Among the remaining DVD players, E is the correct response because it is the one with the highest average rating across each of the features. Each participant's score was computed as the proportion of items in which the correct DVD player was selected according to the specified decision rule.

Consistency in Risk Perception (α = .72; r_{tt} = .51) comprised of 20 items in which participants rated the probability of an event happening to them on a scale of 0% (no chance) to 100% (certain). Ten pairs of items corresponded to the same event occurring in either the next year or the next 5 years. For example, participants were asked, "*What is the probability that you will get into a car accident while driving in the next year?*" and "*What is the probability that you will get in a car accident while driving during the next 5 years?*" These pairs of items were scored as correct if the probability of the event occurring in the next year was less than that of the event occurring in the next 5 years. Next, three pairs of items presented nested subset and superset events. For example, participants were asked, "*What is the probability that someone will steal something from you in the next 5 years?*" and "*What is the probability that someone will break into your home and steal something from you in the next 5 years?*" These pairs of items were scored correct if the probability of the subset event was rated lower than that of the superset event. Lastly, two pairs of items were complementary, such that the combined probability of both events ought to equal 100%. For example, participants were asked, "*What is the probability that you will move your permanent address to another state sometime in the next year?*" and "*What is the probability that you will keep your permanent address in the same state during next year?*" These pairs of items were scored as correct if the participants ratings on each item within a pair summed to 100%. Each participant's total score was calculated as the proportion of correct responses across the pairs of items (i.e., 10 timeframe pairs, 6 subset-superset pairs, and 4 complementary pairs).

Resistance to Sunk Cost ($\alpha = .54$; $r_{tt} = .61$) comprised 10 items, each of which described a situation in which a previous investment is no longer providing value. Participants rated on a 6-point Likert scale their preference for continuing or discontinuing the investment. For example:

> *You are in a hotel room for one night and you have paid $6.95 to watch a movie on pay TV. Then you discover that there is a movie you would much rather like to see on one of the free cable TV channels. You only have time to watch one of the two movies. Would you be more likely to watch the movie on pay TV or on the free cable channel?*

The scale for this question ranges from 1 (most likely to watch pay TV) to 6 (most likely to watch free cable). Scores were calculated as the mean rating across the 10 items.

Principal Analyses

The purpose of this analysis is to examine the relative importance of numeracy and cognitive abilities for predicting decision-making competence in a group of young adults who are preparing for diverse professional careers. Relative importance is defined as “the proportionate contribution each predictor makes to R^2, considering both its direct effect (i.e., its correlation with the criterion) and its effect when combined with the other variables in the regression equation,” (Johnson & LeBreton, 2004, p. 240). Previous research on decision-making competence used multiple regression in which results are described in terms of zero-order correlations and standardized regression coefficients. These estimates can only be used to measure relative importance when predictors are uncorrelated, which is rarely true for mental test scores (Lang et al., 2010). When predictors are uncorrelated, correlations and regression coefficients are equivalent and represent proportionate contributions to the variance predicted by the model. Under multicollinearity, these estimates are interpreted differently. Correlations describe the relationship between each predictor and the criterion by itself, whereas regression coefficients describe the contribution of one predictor when combined with other predictors. Different methods are required to accurately represent how well one predictor contributes to the model when compared to all the combinations of others under multicollinearity.

Several methods have been proposed for estimating relative importance (Nimon & Oswald, 2013). Two of the most commonly used methods in organizational research are (1) relative weights and (2) dominance analysis. Both have been used to examine the relative importance of cognitive abilities in personnel selection (Lang et al., 2010; Lang & Kell, 2019).

Relative weights analysis derives orthogonal variables that are maximally correlated with each of the predictors (Johnson, 2000). These coefficients are combined with coefficients derived from regressing the criterion on the transformed variables, hence producing a robust estimate of relative importance. Dominance analysis follows the logic of estimating regression models with all possible subsets of predictors and making pairwise comparisons between each predictor's incremental contribution to predicted variance in the criterion (Budescu, 1993). Despite relying on different algorithms, relative weights and dominance tend to generate equivalent results (LeBreton et al., 2004). That said, subtle differences between the methods can matter for interpretation.

There are several features unique to dominance analysis make it the preferred approach for the present study. Dominance analysis is theoretically grounded in normative decision theory, specifically the principle of (weak) dominance (Budescu & Azen, 2004). This principle states that one option should be preferred over another if (1) all of its characteristics are at least as good as those of the other and (2) at least one characteristic is better than that of the other. Dominance has been described as "perhaps the most obvious principle of rational choice," (Kahneman & Tversky, 1986). That personnel selection itself is an application of rational decision theory makes this approach conceptually appealing. Dominance analysis is also unique in that it provides multiple frames of reference for estimating relative importance. These frames allow for multiple degrees of support for each of the study hypotheses. Specifically, Azen and Budescu (2003) described three levels of relative importance: complete dominance, conditional dominance, and general dominance. These levels are hierarchically organized with complete dominance as the highest level. Complete dominance encompasses conditional dominance, which encompasses general dominance. Dominance is specified in reference to each pair of predictors.

One predictor is completely dominant over another when its incremental contribution to each subset model is greater than that of the other predictor. The strongest support for Hypothesis 1 would be complete dominance of crystallized or fluid ability over numeracy for predicting decision-making competence. This result would indicate that cognitive ability contributes more toward prediction than numeracy in each combination of predictors. Likewise, a result in which numeracy is completely dominant over both cognitive abilities would be the strongest support for Hypothesis 2. Another possible result involving complete dominance is if either crystallized or fluid ability is completely dominant over the other. Although the focus of this study is on numeracy, information on the relative importance of crystallized and fluid ability could provide additional insight into the cognitive abilities required for normatively superior decision making.

The requirements for complete dominance are strict. All it takes is numeracy contributing more toward prediction than a cognitive ability in one subset model to reject complete dominance. Seeing that a predictor could be dominant over another under different conditions, Azen and Budescu (2003) termed conditional dominance for describing relative importance for sub-models with different numbers of predictors included. For example, numeracy could be the best single predictor of decision-making competence while crystallized ability is the strongest predictor in models involving any pair of the three predictors. Note that estimates of complete and conditional dominance are the same in models with only three predictors.

Lastly, general dominance is the least strict and most intuitive way of grasping the relative importance of predictors. General dominance refers to the average incremental contribution of each predictor over all of the subset models. The sum of general dominance weights adds up to R^2, hence each weight corresponds to a predictor's proportional contribution to prediction. These estimates are comparable to those derived from relative weights analysis (Johnson, 2000). General dominance weights provide an intuitive way of rank ordering the relative importance of variables and making comparisons across different criteria. For example, numeracy could make a larger contribution toward predicting Resistance to Framing than fluid ability while the reverse pattern is true for predicting Applying Decision Rules.

Although the estimates computed by dominance analysis are robust to multicollinearity, they are sensitive to the reliability of the measures being used (Braun et al., 2019). Measurement error can distort the relationships between constructs by attenuating correlations between variables (Nunnally & Bernstein, 1994). To account for measurement error in the dominance analysis, I applied Spearman's correction for attenuation:

$$r_{T_xT_y} = \frac{r_{xy}}{\sqrt{r_{xx'}r_{yy'}}}$$

where r_{xy} is the observed correlation between two variables and $r_{xx'}$ and $r_{yy'}$ are the internal consistency coefficients for each variable, estimated with Cronbach's alpha. However, correcting for measurement error comes with the cost of greater uncertainty in the point estimates (Schmidt & Hunter, 2014). To assess the generalizability of the dominance weights, bootstrapping was applied to estimate confidence intervals (Efron & Tibshirani, 1994).

Dominance analysis was conducted with the *yhat* package in R (Nimon & Oswald, 2013). I conducted a univariate dominance analysis of composite A-DMC scores regressed on numeracy, crystallized, and fluid ability. In addition, I conducted a univariate dominance analysis for each of the A-DMC subscale scores. The analysis produces $2^3 - 1 = 7$ subset models spanning every combination of the three predictors. For comparison, I also conducted hierarchical regressions by regressing composite A-DMC scores and each of the A-DMC dimensions on the set of predictors in two sets of models that differ with respect to the order of the predictors entered. In one set, I examined the incremental validity of numeracy over cognitive abilities by entering fluid and crystallized ability into the model first, followed by numeracy. In the second set, I examined the incremental validity of cognitive abilities over numeracy by entering numeracy into the model first, followed by fluid and crystallized ability.

Results

Descriptive statistics are displayed in Table 1. Score distributions and reliability coefficients were consistent with prior research on the A-DMC (Blacksmith et al., 2019; Bruine de Bruin et al., 2007; Del Missier et al., 2012). Internal consistency for DMC was acceptable (α = .79), though it should be noted that this estimate corresponds to a model in which each of the A-DMC items loaded on a general factor. An alternative model in which sub-scale scores were the indicator variables had much lower internal consistency (α = .39).

Correlations between the study variables are displayed in Table 2. All predictors were significantly correlated with the A-DMC and each of its subscales, with two exceptions. Fluid ability was not significantly correlated with Consistency in Risk Perception or Resistance to Sunk Cost.

Measurement Models

Measurement models for each predictor and criterion were examined via confirmatory factor analysis (CFA) with the *lavaan* package in R version 4.0 (Rosseel, 2012). Model fit was evaluated using variety of fit indices based on Hu and Bentler's (1999) recommendations. The chi-square goodness of fit test estimates the difference between observed and expected covariance matrices. Conventionally, a chi-square statistic with a *p*-value less than .05 is considered acceptable fit, but this estimate is sensitive to sample size. The comparative fit index (CFI) compares the specified model to a null model and is less sensitive to sample size. CFI values above .90 are considered acceptable fit (Hu & Bentler, 1999). Both the standardized root mean square residual (SRMR) and root mean square error of approximation (RMSEA) are variations of evaluating how well the specified model represents the observed variance–covariance matrix. Hu and Bentler (1999) recommended cut-off values of ≤ .06 for SRMR and ≤ .08 for RMSEA to indicate acceptable fit. Note that many alternative recommendations for interpreting fit statistics are available, and that model fit is only one consideration in model evaluation (Loehlin & Beaujean, 2017). Hu and Bentler's (1999) recommendations were chosen because they are commonly used in the psychological literature.

Although the present study is focused on the criterion-related validity of numeracy, measurement invariance is important to consider when evaluating measures for use in personnel selection. Measurement invariance is the characteristic of a measure that has the same psychometric structure between subgroups. Variation in this structure can undermine inferences about subgroup differences on the underlying construct. To test measurement invariance across gender for each of the variables, I followed the stepwise procedure described by Widaman and Reise (1997). In order, I tested for configural, metric, scalar, and strict invariance, which correspond to equal factor structure, factor loadings, intercepts, and residual variances, respectively. Ideally, tests of measurement invariance would also be conducted between the samples and racial and ethnic subgroups. However, with the exception of gender, the sample sizes of these subgroups (e.g., 24 participants who self-reported as Black or African American, 46 participants from the MTU sample) were too small to make meaningful inferences (Meade & Bauer, 2007).

Numeracy and cognitive abilities

Single-factor models were a good fit for crystallized ability (Table 3) and numeracy (Table 5) according to each of the fit indices. The measurement model of fluid ability was a good fit to the data according to the RMSEA and SRMR, but not the CFI (Table 4). Prior to estimating the measurement model of crystallized ability, some modifications were required for the model to be properly specified. First, responses to three items were excluded because none of the participants answered them correctly (i.e., the variance was zero). Next, the remaining 47 items were aggregated into 10 parcels of 4-5 items each using an item-to-construct balancing approach (Little et al. (2002). Parceling is recommended for scales with large numbers of items, which can otherwise cause estimation problems. Metric invariance held for both numeracy and crystallized ability, but not scalar invariance (Tables 3, 5). Only configural variance held for fluid ability (Table 4).

Decision making competence

The one-factor model of DMC was estimated with each of the sub-scale scores as indicators. This model was an acceptable fit to the data according to the RMSEA and SRMR, but not the CFI (Table 6). Nevertheless, it passed all tests of measurement invariance. One-factor models were estimated for each of the A-DMC dimensions except for Recognizing Social Norms, which due to its unique scoring approach, does not lend itself to factor analysis. Applying Decision Rules was the only model with good fit according to each of the indices and passed all tests of measurement invariance (Table 9). Resistance to Framing (Table 7) and Under/Overconfidence (Table 8) demonstrated less than optimal model fit according to the CFI, but acceptable fit according to the RMSEA and SRMR. Neither of these two measures passed tests of configural invariance. Consistency in Risk Perception had poor fit according to each of the fit indices and failed the test of configural invariance. The model for Resistance to Sunk Cost did not converge, presumably due to its especially low internal consistency.

A common theme among most of the measurement models was acceptable fit according to the RMSEA and SRMR, but poor fit according to the CFI. There are multiple potential explanations for this discrepancy, in which a full investigation is beyond the scope of this study. One likely reason is due to low correlations among the indicator variables, which is apparent in many of the A-DMC subscales. See Lai and Green (2016) for a discussion of inconsistencies between fit indices in CFA models.

Dominance Analyses

To address the research questions and hypotheses, I estimated the relative importance of numeracy, crystalized, and fluid ability for predicting decision making competence and each of its dimensions. I conducted univariate dominance analyses on the correlations corrected for measurement error (see Appendix A for analyses on the observed correlations). Levels of dominance were inferred from the point estimates (Azen & Budescu, 2003). However, bootstrapping results provide additional information on estimate precision (Braun et al., 2019). Both sets of dominance analysis results are displayed for each of the criteria in Tables 11-24. Odd-numbered tables display the R^2 of each submodel and the incremental R^2 of each predictor to that submodel. These tables also report the general dominance weights, which are re-scaled as percentages of the total variance explained (R^2) by the model with all predictors. The even-numbered tables display the dominance levels for each pair of predictors and their accompanying bootstrap results. The following section describes the highest level of dominance observed for each predictor across the dimensions of decision-making competence. Hypothesis 1 and 2 predicted a consistent pattern of relative importance across each of the dimensions, whereas

Hypothesis 3 predicted a varying pattern. Provided that many studies report only the general dominance weights (e.g., Lang & Kell, 2019), these estimates will be the basis for testing the hypotheses. That being said, the higher levels of dominance and bootstrapped confidence intervals provide additional information regarding the strength of support.

For overall decision-making competence, that is, the unit-weighted average of scores on the six A-DMC subscales, the predictors accounted for 27% of the variance (Table 11). Numeracy and crystallized ability each accounted for 40% of the model-explained variance, while fluid ability accounted for the remaining 20%. Both numeracy and crystallized ability were completely dominant over fluid ability (Table 12). Numeracy was also generally dominant over crystallized ability. Hypothesis 1 predicted that numeracy is not relatively important for predicting decision-making competence compared to crystallized and fluid ability, whereas Hypothesis 2 stated the numeracy is relatively important. That numeracy was at least generally dominant over both cognitive abilities in this analysis supports Hypothesis 2. However, note that the general dominance of numeracy over crystalized ability replicated in only 54% of the bootstrapped samples (Table 12). By this measure, numeracy and crystallized ability seem to make approximately equal contributions to overall decision-making competence. Nevertheless, the point estimates of relative importance support Hypothesis 2 over Hypothesis 1, showing that numeracy is relatively important for predicting decision-making competence compared to crystallized and fluid ability.

Total explained variance and the relative importance of each predictor varied across each of the dimensions of decision-making competence. Altogether, the predictors accounted for 25% of the variance in Resistance to Framing (Table 13). Numeracy accounted for 56% of the model-explained variance, followed by 32% and 13% corresponding to fluid and crystallized ability, respectively. Numeracy was completely dominant over crystallized and fluid ability for predicting Resistance to Framing, which was observed in 100% and 89% of the bootstrapped samples, respectively (Table 14). Moreover, fluid ability was completely dominant over crystallized ability in almost 100% of the bootstrapped samples.

Of the small amount of variance ($R^2 = .04$) in Recognizing Social Norms explained by the predictors, numeracy and crystallized ability each accounted for approximately 47% and 39% respectively. The remaining 14% was accounted for by fluid ability (Table 15). Crystallized ability was completely dominant over numeracy and fluid ability for predicting Recognizing Social Norms (Table 16). Also, numeracy was completely dominant over fluid ability.

Together, the predictors accounted for 13% of the variance in Under/Overconfidence, a majority of which (78%) was explained by crystallized ability (Table 17). Numeracy and fluid ability accounted for 15% and 7% of this variance, respectively. Crystallized ability was completely dominant over numeracy and fluid ability for predicting Under/Overconfidence (Table 18). This result occurred in 100% of the bootstrapped samples. Again, numeracy was completely dominant over fluid ability (Table 18).

The predictors accounted for 61% of the model-explained variance in Applying Decision Rules—the most of any of the dimensions (Table 19). Numeracy accounted for 36% of this variance while crystallized and fluid ability accounted for 31% and 33%, respectively. Numeracy was completely dominant over crystalized ability for predicting Applying Decision Rules, which occurred in 57% of the bootstrapped samples (Table 20). Numeracy and crystallized ability were both generally dominant over fluid ability. The general dominance of numeracy over both cognitive abilities occurred in more than 80% of the bootstrapped samples.

The predictors accounted for 7% of the variance in Consistency in Risk Perception, 57% of which was attributed to crystallized ability (Table 21). Numeracy and fluid ability accounted for the remaining 29% and 14%, respectively. For predicting Consistency in Risk Perception, Numeracy was completely dominant over fluid ability, whereas crystallized ability was completely dominant over fluid ability and numeracy (Table 22). The complete dominance of crystallized ability over numeracy occurred in 80% of the bootstrapped samples.

The predictors also accounted for 7% of the variance in Resistance to Sunk Cost (Table 23). Numeracy accounted for 57% of the model-explained variance, followed by crystallized and fluid ability, with 29% and 14% respectively. Numeracy was completely dominant over crystallized and fluid ability, and crystallized ability was completely dominant over fluid ability (Table 24). The complete dominance of numeracy over crystallized ability occurred in 69% of the bootstrapped samples and that over fluid ability occurred in 93%.

In accord with what was previously mentioned with respect to overall decision-making competence, taken together all the dominance analyses results clearly refuted Hypothesis 1, which stated that numeracy is not relatively important for predicting decision-making competence compared to crystallized and fluid ability. Rather, the results were supportive of Hypothesis 2, which stated that numeracy is relatively important over cognitive abilities for predicting decision-making competence. Ultimately, however, the dominance analyses showed support for Hypotheses 3, which stated that the relative importance of numeracy over cognitive abilities varies across different dimensions of decision-making competence. While numeracy consistently outperformed fluid ability in almost every model, the importance of numeracy relative to crystallized ability varied across dimensions. Numeracy was completely dominant over crystallized ability for predicting Resistance to Framing, Applying Decision Rules, and

Resistance to Sunk Cost. The opposite pattern was observed for Recognizing Social Norms, Under/Overconfidence, and Consistency in Risk Perception. A summary of the levels of dominance is displayed in Table 25 and a summary of the rescaled general dominance weights (percentage of variance explained in the criterion explained by each predictor) is displayed in Figures 1 and 2.

Hierarchical Regression Analyses

In comparison to the results for the dominance analyses, I examined the incremental validity of the numeracy beyond the cognitive ability test scores and demographic variables using multiple regression analyses on the correlations corrected for measurement error. Specifically, I estimated a hierarchical regression model for each criterion in which university sample, gender, crystallized, and fluid ability were included in the first step, and numeracy was added in the second step. A statistically significant change in variance explained (ΔR^2) was interpreted as evidence for the incremental validity of numeracy. In addition, I estimated a set of models that tested the incremental validity of crystalized and fluid ability over numeracy. A statistically significant ΔR^2 in these models signaled the incremental validity of cognitive abilities beyond numeracy for predicting each criterion.

Hierarchical regression models of decision-making competence and its dimensions are reported in Tables 26-32. Numeracy demonstrated incremental validity over crystallized and fluid ability for predicting overall decision-making competence, Resistance to Framing, Applying Decision Rules, and Resistance to Sunk Cost. These results provided additional support for Hypothesis 3. The incremental validity of numeracy over cognitive abilities varied across dimensions of decision-making competence. Moreover, the pattern of incremental validity for crystallized and fluid ability varied across the dimensions.

Discussion

The purpose of the present study was to evaluate the relative importance of statistical numeracy for decision-making competence relative to crystallized and fluid ability. Competing hypotheses addressed a pair of research questions about (1) the extent to which numeracy is relatively important to cognitive abilities for making decisions and (2) the extent to which the relative importance of these constructs varies across dimensions of decision making. The results supported the overall conclusion that numeracy is relatively important over cognitive abilities, and that its relative importance varies across dimensions. Specifically, numeracy was at least generally dominant over crystallized and fluid ability for predicting decision-making competence. Numeracy also outperformed fluid ability across each of the dimensions of decision-making competence, although at different levels of dominance. The relative importance of numeracy over crystallized ability varied across the dimensions. These results provide insight into the roles of numeracy and cognitive abilities for explaining individual differences in decision-making competence. Each variable makes an important and unique contribution, which further illustrates the multidimensional nature of decision-making competence.

These results are largely consistent with previous studies examining the roles of numeracy and cognitive abilities in decision making (e.g., Blacksmith et al., 2019; Cokely et al., 2012; Del Missier et al., 2012). Building on this research, the present study offers several theoretical and practical contributions to the literature on decision making in the workplace. First, the present study leveraged statistical methods that address challenges associated with the multicollinearity of predictors. Scores on tests of numeracy and cognitive abilities like crystallized and fluid ability are strongly correlated with each other, which can complicate inferences regarding any specific variable. Dominance analysis with corrections for measurement error enabled the disentangling of predictors' relative importance for predicting decision-making competence. Moreover, I examined decision-making competence as a multidimensional construct by estimating separate models for each dimension. These dimensions reflect a broad range of criteria drawn from the psychology of decision-making, which correspond to different elements of workplace decisions. This is a key contribution this study, given that my literature search did not reveal any prior studies that examined the extent to which numeracy's relative importance varied across specific dimensions of decision-making competence.

The present study has practical implications for the use of assessment in personnel selection and job placement. Little research has tied the literature on judgment and decision making to that of I/O psychology, making this study a novel contribution to a small, but growing subdiscipline (Zhang & Highhouse, 2018). Making good decisions is an increasingly important competency as the workplace becomes more complex. These results demonstrated not only that traditional cognitive ability tests cannot fully account for decision-making competence, but also that numeracy tests are viable tools for assessment. Using these results as a foundation, further research can further specify the construct domain of decision-making competence and the knowledge, skills, and abilities that facilitate decision making.

Theoretical Implications

Numeracy was completely dominant over fluid ability for predicting decision-making competence and five out of six of its dimensions. The exception was Applying Decision Rules, for which numeracy was still generally dominant over fluid ability. This result is consistent with many studies in which numeracy was shown to have incremental validity over fluid ability in various decision-making tasks (e.g., Cokely et al., 2012; Peters et al., 2006). In contrast to research that emphasizes the role of information-processing capacities for decision making, these results indicate that tests of fluid ability may be less useful in assessment contexts. Fluid ability tests are often weaker predictors relative to crystallized ability tests (Larson, 2019; Postlethwaite, 2011). One explanation for this is Brunswik symmetry: the principle that constructs aligned in terms of breadth and specificity are more strongly related (Brunswik, 1955). Although fluid ability is theorized to be a critical part of developing crystallized ability and numeracy, it is a distal predictor whereas the latter constructs are more proximally related to decision making.

Determining the relative importance of numeracy over crystallized ability was more challenging, considering how these variables seem to share common sources of variance. Indeed, people who acquire higher levels of crystallized ability are likely to demonstrate higher numeracy as well. However, note that even highly educated professionals can demonstrate low numeracy (Cokely et al., 2012; Schwarz et al., 1993). Skilled decision theory describes the relationship between numeracy and decision making as mediated by risk literacy, or relevant knowledge to the decision context (Cokely et al., 2018; Gigerenzer, 2015). Numeracy is expected to facilitate a metacognitive savvy for decision-making scenarios beyond general knowledge. However, this savvy may be more or less important depending on the kinds of processes elicited by the decision situation or the values of the person making the decision.

Of all the dimensions of decision-making competence, numeracy had the strongest estimates of relative importance for Resistance to Framing. This result is consistent with many studies on numeracy and decision making, which examined individual differences in framing effects (Gamliel et al., 2016; Gamliel & Kreiner, 2017; Peters et al., 2006; Peters & Levin, 2008). Indeed, people with higher numeracy are less susceptible to framing effects, possibly due to assigning more affective meaning to numbers instead of irrelevant information. A key part of this explanation can be attributed to the transfer of identical elements. Items that comprise

Resistance to Framing the most explicit reference to numbers of all the A-DMC items. To earn a high score, one must recognize that ground beef with 20% fat is the same as that which is 80% lean, for example. Framing is ubiquitous in organizations, where information can be portrayed in ways that persuade or mislead, whether intentionally or not. Numeracy is a valued skill that enables one to recognize objective, quantitative aspects of communications.

In contrast, neither numeracy nor fluid ability appeared to be especially influential for predicting Under/Overconfidence. Crystallized ability outperformed the other variables by far when predicting this dimension. Judging by the assessment content, the Under/Overconfidence scale of the A-DMC is essentially a general knowledge test accompanied by subjective ratings of performance. Crystallized ability is a broad construct that corresponds to general knowledge that one acquires throughout their life. Volumes of scholarly papers have been written on the finding that people with greater competence are better at judging their competence (Kruger & Dunning, 1999; Gignac & Zajenkowski, 2020). Previously, numeracy has been shown to be related to confidence calibration (Ghazal et al., 2014). Although this relationship may be attributed to the shared variance between numeracy and crystallized ability, the result is still consistent with skilled decision theory. In particular, people with a representative understanding of the information relevant to a decision are "risk literate" and likely to perform better across a variety of tasks that involve some degree of a risk-reward tradeoff (Cokely et al., 2018).

While Resistance to Framing and Under/Overconfidence were clearly predicted by one cognitive variable that was dominant over the others, Applying Decision Rules appeared to be the product of equal contributions from all three predictors. The combination of numeracy and crystallized and fluid ability contributed the largest R^2 toward predicting Applying Decision Rules than any other dimension. Variance accounted for in the criterion was split equally among each of the predictors according to the general dominance weights, indicating that numeracy, crystallized, and fluid ability each make important contributions toward choosing the best option from a set of alternatives in accordance with normative decision criteria. Individual differences in decision making are undoubtedly the result of many facets of knowledge, skills, and abilities. Rosi et al. (2019) also found unique contributions of information-processing and knowledge-based predictors on Applying Decision Rules. In their study, age differences were attributed to age-related declines in attentional processes related to fluid ability. However, acquired general knowledge can compensate for lower fluid ability (Mata et al., 2012). Numeracy is another important piece of the construct domain, as it enables more efficient deliberation of decision rules (Cokely & Kelley, 2009). There is no single path toward making better decisions. That numeracy and cognitive abilities make unique contributions toward decision-making competence is consistent with the notion of equifinality—that multiple strategies can lead to similar outcomes (Cokely & Kelley, 2009; Cokely et al., 2006).

Making inferences about the remaining three dimensions (i.e., Recognizing Social Norms, Consistency in Risk Perception, and Resistance to Sunk Cost) is more challenging considering that even the full set of predictors accounted for a negligible amount of variance in each criterion. Like overall decision-making competence, numeracy and crystallized ability accounted for most of the explained variability in these dimensions. One contribution of this dissertation was the examination of each of the dimensions of decision-making competence, which are usually examined either exclusively in aggregate or piecemeal. In the case of Recognizing Social Norms, Consistency in Risk Perception, and Resistance to Sunk Cost, two explanations seem likely for explaining these results. These factors may be attributed to personality or motivational variables beyond cognitively loaded variables like those in the present study. Moreover, more reliable measurement of these constructs may be required to draw robust inferences.

Of the small amount of variance explained in Recognizing Social Norms, crystallized ability was completely dominant over numeracy and fluid ability. This indicates that general acquired knowledge may be relatively important for making accurate perceptions of others' attitudes and behaviors. Weaker relationships with numeracy and cognitive abilities have been observed for this dimension (Blacksmith et al., 2019; Del Missier et al., 2012). Recognizing Social Norms might be further influenced by broad personality traits such as agreeableness and social interests as classified by the RIASEC framework of vocational interests (Wille & De Fruyt, 2014) and more specific aspects of personality like self-monitoring (Snyder, 1974). People who are motivated to invest their knowledge, skills, and abilities into understanding social environments are likely better at detecting shared perceptions and subsequently making better decisions derived from those judgments (Ackerman & Heggestad, 1997).

Crystallized ability was also completely dominant for predicting a small amount of variance in Consistency in Risk Perception. This dimension of decision-making competence reflects the ability to maintain risk perceptions consistent with normative decision theory (e.g., the risk of event A and B is less than event A or B). Contrary to these results, other studies have reported stronger relationships between cognitive abilities and Consistency in Risk Perception (Blacksmith et al., 2019; Del Missier et al., 2012). Del Missier et al. (2012) observed stronger relationships with tasks designed to explicitly assess memory and attentional processes. Although these constructs are strongly related to fluid ability, memory, attention, and executive functions more broadly may facilitate making judgments about risk (Ackerman et al., 2005).

Consistency in Risk Perception may also be influenced by general or domain-specific attitudes toward risk (Highhouse et al., 2017).

Lastly, numeracy was completely dominant over cognitive abilities for predicting Resistance to Sunk Cost, albeit a small proportion of variance. The strength of relationships between cognitive abilities and this dimension varies across studies (Blacksmith et al., 2019; Bruine de Bruin et al. 2007). Age seems to be an influential variable to Resistance to Sunk Cost in a way that is weakly related to cognitive abilities (Del Missier et al., 2015; Strough et al., 2016). Strough et al. (2016) suggested that individual differences in sunk cost effects might be attributed to one's future orientation. Younger people are generally more likely to be optimistic about a plan's outcomes and are thus more likely to assign value to past commitments. Given the adaptive nature of sunk costs, relationships with knowledge, skills, and abilities might be sensitive to interactions between the individual and organizational context.

Practical Implications

That numeracy emerged as a robust predictor across many of the models in this study supports the utility of numeracy tests for personnel selection and job placement. A growing literature in recent years has called for investigations into specific cognitive abilities (Scherbaum et al., 2012). This contrasts with a tradition among I/O psychologists to emphasize the utility of GMA over other predictors (e.g., Ree & Earles, 1991). As the workplace continues to increase in complexity, more nuanced assessment is necessary to adequately match potential employees to jobs in which they are most likely to succeed. The skills necessary to make decisions under risk and uncertainty will continue to be important for work performance. However, direct assessments of decision-making, including low-fidelity simulations and work samples, can be cumbersome, expensive to develop, and time consuming. The present results indicate that numeracy, as measured by the 5-to-10-minute Berlin Numeracy Test is potentially an effective proxy of decision-making skill for assessment purposes.

Numeracy can also be leveraged for personnel training systems (Fong et al., 1986; Fong & Nisbett, 1991; Gigerenzer, 2015). Whereas the cognitive ability is generally conceptualized as a rather stable disposition that stems from individual differences in early cognitive development, statistical numeracy is an acquired skill. As such, education and training can be leveraged to improve workers' numeracy. Skilled decision theory asserts that numeracy training can transfer to better general decision making due to identical elements between cognitive processes for comprehending risk and uncertainty. In contrast, there is little evidence that training cognitive ability transfers beyond the tests practiced by trainees (Sala & Gobet, 2017; Sala et al., 2019; Simons et al., 2016). This dissertation speaks to the underlying causes and malleability of decision-making skills at work.

This dissertation conceptually linked the dimensions of decision-making competence to the workplace environment. That numeracy was shown to uniquely predict decision-making competence suggests opportunities for context-specific applications in organizations. Synthetic validation is the process of estimating validity on the basis of similarities in job components and the required competences between jobs (Johnson & Carter, 2010; Scherbaum, 2005). Provided that jobs have similar decision-making environments, practitioners could generalize validation studies from one job to another. This process could determine the optimal weighting of numeracy and cognitive abilities used in assessment. The multidimensional nature of decision-making competence can be used as a guiding post for job and task analyses aimed at eliciting the decision-making context and competencies for a given job. Links between numeracy and job demands might not be explicit (Black et al., 2015). Thus, targeting decision-making processes in job or task analysis may have promise for detecting the links between job demands and predictor constructs, which in turn can inform how to best leverage numeracy in personnel selection systems and training programs. More generally, there is still lots of progress to be made with respect to squarely focusing on decision-making competence in the workplace. Many opportunities are available for integrating concepts and methods from I/O psychology and the psychology of judgment and decision making.

Limitations and Future Directions

There are limitations to consider when interpreting the results of the present study. Like many psychological studies, there are challenges associated with generalizing results from samples to the broader population. This dissertation aims to make inferences about working populations, yet the sample is comprised of undergraduate students. Nevertheless, many of these students are young adults who will move on to diverse professional careers. By combining a pair of samples from different universities, the results are slightly more representative of the heterogeneous population than if one sample was used. Due to insufficient sample size, I was unable to test measurement invariance between these samples. However, it is worth noting that in separate set of analyses excluding the 46 MTU students from the analysis the pattern of results was largely consistent with those in the combined sample.

Perhaps the most difficult issue for this research is the criterion problem (Austin & Villanova, 1992). Although the A-DMC covers a broad span of the normative decision criterion domain, the nature of what makes a good decision is a complex matter that can vary substantially based on a person’s values or level of expertise (Gigerenzer, 1996; Yates, 2003). This study relied on the assessment of theoretically guided decision-making skills among undergraduate students. Little research on decision making constructs in the workplace has been conducted from the perspective of assessment validation (Lake & Highhouse, 2013). Future research should acknowledge the domain-specific nature of skilled decision making by adopting job and task analysis of decision processes that are frequently encountered in the workplace. This research can help scope an ecologically valid criterion domain, which could subsequently be translated into situational judgment tests or work samples. Both low- and high-fidelity simulations could be used as criterion measures in future validation studies of numeracy tests (Arthur & Villado, 2008; Van Iddekinge & Ployhart, 2008).

Additional insights could be gained by expanding the predictor construct domain as well. Crystallized and fluid ability are two of the broadest dimensions of Carroll's (1993) model of cognitive abilities, which also includes specific abilities and domains of knowledge that could emerge as relatively important for decision making. Whereas the present study relied on fluid ability as the measure of general information-processing capabilities, other researchers have advocated for the use of working memory and executive function assessments (Bosco et al., 2015). Whereas crystallized and fluid ability are theoretically broader, tests of numeracy correspond to narrower factors such as quantitative ability or even domain-specific knowledge. Moreover, additional research is needed on the composition of numeracy and how it relates to decision-making. Although this study used a well-established test of numerical abilities, we did not include any established measures explicitly used to assess quantitative reasoning as reflected in the Carroll's (1993) model (e.g., number series).

Even the construct domain of numeracy comprises multiple dimensions beyond those included in the present study. The Berlin Numeracy Test is supported by a large corpus of validation evidence reported in the literature (Cokely et al. 2018). Statistical numeracy is the strongest single predictor of general decision-making skill, although other components of numeracy (e.g., algebra, geometry, operations) may be relatively important for particular elements of decision making. Peters and Bjalkebring (2015) emphasized the roles of subjective numeracy and approximate number sense in addition to objective numeracy. Sobkow et al. (2020) conducted a study similar to this one, in which they assessed the relative importance of multiple numeric competencies and cognitive abilities on self-reported decision outcomes. Approximate number sense emerged as the strongest predictor, which emphasizes a different aspect of skilled decision theory. Extrapolating on Sobkow et al.'s (2020) results, people with a greater intuitive sense of discrepancies between quantities may be able to more quickly and effectively focus on decision-relevant information.

Rationality is conceptualized as a broad construct that spans motivational characteristics in addition to cognitive variables (Stanovich et al., 2016). One of the most frequently studied variables in the study of individual differences in decision making is cognitive reflection, defined as the tendency to override intuitive judgments. The cognitive reflection test (CRT) is cognitively loaded and strongly correlated with numeracy to such an extent that it remains unclear what distinct constructs are being measured by the CRT (Patel, 2017). Building on the present study, research is likely to draw further insights by simultaneously evaluating multiple domains of knowledge, skills, and abilities to understand decision-making.

Lastly, this dissertation made statistical inferences based on correlations corrected for attenuation. This approach is used by psychologists to identify the relationships between variables in a hypothetical world void of measurement error (e.g., Schmidt & Hunter, 1998). Although this approach enables the conceptual comparison of predictor validities, measurement error is the reality in application. Dominance analyses and hierarchical regression models based on the uncorrected correlations are reported in Appendix A and B, respectively. Patterns of results are largely comparable when acknowledging uncertainty in the point estimates, though relative importance coefficients were larger for cognitive abilities without corrections, which also had larger reliability coefficients. Future work on the viability of numeracy assessments in the workplace should consider the operational validities for making personnel decisions.

Conclusion

As the workplace grows in complexity, the knowledge, skills, and abilities required to make good decisions will continue to be vital. I/O psychology can benefit from the study of judgment and decision making by joining these concepts with those of personnel selection and assessment. The present study is a proof of concept that although many cognitive abilities are involved in decision making, numeracy is a well-defined and important predictor of decision-making competence. Numeracy accounts for variability in decision-making competence that is unique from traditional tests of cognitive abilities. Organizations may benefit from assessing numeracy in the workplace, or perhaps more importantly, conducting job analyses and validation studies that reveal the numerical demands that are common to different kinds of workplace decisions. Numeracy tests are not guaranteed to substitute for cognitive ability tests, but could make up an important supplement to commonly used test batteries in selection systems for jobs that involve a high degree of decision making.

References

Ackerman, P. L. (1988). Determinants of individual differences during skill acquisition: Cognitive abilities and information processing. *Journal of Experimental Psychology: General*, *117*(3), 288–318. https://doi.org/10.1037/0096-3445.117.3.288

Ackerman, P. L., Beier, M. E., & Boyle, M. O. (2005). Working memory and intelligence: The same or different constructs? *Psychological Bulletin*, *131*(1), 30–60. http://doi.org/10.1037/0033-2909.131.1.30

Ackerman, P. L., & Heggestad, E. D. (1997). Intelligence, personality, and interests: Evidence for overlapping traits. *Psychological Bulletin*, *121*(2), 219–245. http://doi.org/10.1037/0033-2909.121.2.219

Allan, J. N. (2018). *Numeracy vs. intelligence: A model of the relationship between cognitive abilities and decision making*. https://shareok.org/handle/11244/299906

American Educational Research Association, American Psychological Association, & National Council on Measurement in Education. (2014). *Standards for educational and psychological testing*. American Educational Research Association.

Arthur, W., & Villado, A. J. (2008). The importance of distinguishing between constructs and methods when comparing predictors in personnel selection research and practice. *Journal of Applied Psychology*, *93*(2), 435–442.

Ashby, N. J. S. (2017). Numeracy predicts preference consistency: Deliberative search heuristics increase choice consistency for choices from description and experience. *Judgment and Decision Making*, 12.

Austin, J. T., & Villanova, P. (1992). The criterion problem: 1917–1992. *Journal of Applied Psychology*, *77*(6), 836–874. https://doi.org/10.1037/0021-9010.77.6.836

Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, *118*(4), 1279–1333. https://doi.org/10.1162/003355303322552801

Azen, R., & Budescu, D. V. (2003). The dominance analysis approach for comparing predictors in multiple regression. *Psychological Methods*, *8*(2), 129–148. http://dx.doi.org.ezproxy.lib.ou.edu/10.1037/1082-989X.8.2.129

Bago, B., & De Neys, W. (2020). Advancing the specification of dual process models of higher cognition: A critical test of the hybrid model view. *Thinking & Reasoning*, *26*(1), 1–30. https://doi.org/10.1080/13546783.2018.1552194

Beck, J. W., Scholer, A. A., & Schmidt, A. M. (2017). Workload, risks, and goal framing as antecedents of shortcut behaviors. *Journal of Business and Psychology*, *32*(4), 421–440. https://doi.org/10.1007/s10869-016-9450-0

Black, S., Yasukawa, K., & Brown, T. (2015). The literacy and numeracy 'crisis' in Australian workplaces: Discursive rhetoric vs. production floor realities. *Journal of Education and Work*, *28*(6), 607–630. https://doi.org/10.1080/13639080.2013.854875

Blacksmith, N., Behrend, T. S., Dalal, R. S., & Hayes, T. L. (2019). General mental ability and decision-making competence: Theoretically distinct but empirically redundant. *Personality and Individual Differences*, *138*, 305–311. https://doi.org/10.1016/j.paid.2018.10.024

Bors, D. A., & Stokes, T. L. (1998). Raven's advanced progressive matrices: Norms for first-year university students and the development of a short form. *Educational and Psychological Measurement*, *58*(3), 382–398. https://doi.org/10.1177/0013164498058003002

Bosco, F., Allen, D. G., & Singh, K. (2015). Executive attention: An alternative perspective on general mental ability, performance, and subgroup differences. *Personnel Psychology*, *68*(4), 859–898. https://doi.org/10.1111/peps.12099

Braun, M. T., Converse, P. D., & Oswald, F. L. (2019). The accuracy of dominance analysis as a metric to assess relative importance: The joint impact of sampling error variance and measurement unreliability. *Journal of Applied Psychology*, *104*(4), 593–602. http://dx.doi.org.ezproxy.lib.ou.edu/10.1037/apl0000361

Brooks, M. E., & Pui, S. Y. (2010). Are individual differences in numeracy unique from general mental ability? A closer look at a common measure of numeracy. *Individual Differences Research*, *8*(4), 257–265.

Bruine de Bruin, W., Parker, A. M., & Fischhoff, B. (2007). Individual differences in adult decision-making competence. *Journal of Personality and Social Psychology*, *92*(5), 938–956. https://doi.org/10.1037/0022-3514.92.5.938

Bruine de Bruin, W., Parker, A. M., & Fischhoff, B. (2020). Decision-making competence: More than intelligence? *Current Directions in Psychological Science*, 20.

Bruine de Bruin, W., Strough, J., & Parker, A. M. (2014). Getting older isn't all that bad: Better decisions and coping when facing "sunk costs." *Psychology and Aging*, *29*(3), 642–647. https://doi.org/10.1037/a0036308

Brunswik, E. (1955). Representative design and probabilistic theory in a functional psychology. *Psychological Review*, *62*(3), 193–217. https://doi.org/10.1037/h0047470

Budescu, D. V. (1993). Dominance analysis: A new approach to the problem of relative importance of predictors in multiple regression. *Psychological Bulletin*, *114*(3), 542–551. https://doi.org/10.1037/0033-2909.114.3.542

Budescu, D. V., & Azen, R. (2004). Beyond global measures of relative importance: Some insights from dominance analysis. *Organizational Research Methods*, *7*(3), 341–350. https://doi.org/10.1177/1094428104267049

Campbell, J. P., & Wiernik, B. M. (2015). The modeling and assessment of work performance. *Annual Review of Organizational Psychology and Organizational Behavior*, *2*(1), 47–74. https://doi.org/10.1146/annurev-orgpsych-032414-111427

Carroll, J. (1993). *Human cognitive abilities: A survey of factor-analytic studies*. Cambridge, England: Cambridge University Press.

Ceschi, A., Costantini, A., Phillips, S. D., & Sartori, R. (2017). The career decision-making competence: A new construct for the career realm. *European Journal of Training and Development*, *41*(1), 8–27. https://doi.org/10.1108/EJTD-07-2016-0047

Ceschi, A., Costantini, A., Sartori, R., Weller, J., & Di Fabio, A. (2019). Dimensions of decision-making: An evidence-based classification of heuristics and biases. *Personality and Individual Differences*, *146*, 188–200. https://doi.org/10.1016/j.paid.2018.07.033

Ceschi, A., Demerouti, E., Sartori, R., & Weller, J. (2017). Decision-making processes in the workplace: How exhaustion, lack of resources and job demands impair them and affect performance. *Frontiers in Psychology*, *8*. https://doi.org/10.3389/fpsyg.2017.00313

Chao, G. T., O'Leary-Kelly, A. M., Wolf, S., Klein, H. J., & Gardner, P. D. (1994). Organizational socialization: Its content and consequences. *Journal of Applied Psychology*, *79*(5), 730.

Cokely, E. T., Feltz, A., Ghazal, S., Allan, J., Petrova, D., & Garcia-Retamero, R. (2018). Decision making skill: From intelligence to numeracy and expertise. In K. A. Ericsson, N. Charness, P. J. Feltovich, & R. R. Hoffman (Eds.), *Cambridge Handbook of Expertise* *and Expert Performance* (2nd ed.). Cambridge University Press.

Cokely, E. T., Galesic, M., Schulz, E., Ghazal, S., & Garcia-Retamero, R. (2012). Measuring risk literacy: The Berlin Numeracy Test. *Judgment and Decision Making*, *7*(1), 25–47.

Cokely, E. T., & Kelley, C. M. (2009). Cognitive abilities and superior decision making under risk: A protocol analysis and process model evaluation. *Judgment and Decision Making, 4*(1), 20–33.

Cokely, E. T., Kelley, C. M., & Gilchrist, A. L. (2006). Sources of individual differences in working memory: Contributions of strategy to capacity. *Psychonomic Bulletin & Review, 13*(6), 991–997. https://doi.org/10.3758/BF03213914

Corbin, J., McElroy, T., & Black, C. (2010). Memory reflected in our decisions: Higher working memory capacity predicts greater bias in risky choice. Judgment and Decision Making, 5(2), 110-115.

Dantzig, T., & Mazur, J. (2007). *Number: The language of science*. New York, NY: Plume.

Dawkins, R., & Carlisle, T. R. (1976). Parental investment, mate desertion and a fallacy. *Nature*, *262*(5564), 131–133. https://doi.org/10.1038/262131a0

Del Missier, F., Mäntylä, T., & Nilsson, L. G. (2015). Aging, memory, and decision making. In T. Hess, J. Strough, and C. Löckenhoff (Eds). *Aging and Decision Making: Empirical and Applied Perspectives* (pp. 127–149). San Diego, CA: Elsevier Academic Press.

Del Missier, Fabio, Mäntylä, T., & Bruine de Bruin, W. (2010). Executive functions in decision making: An individual differences approach. *Thinking & Reasoning*, *16*(2), 69–97. https://doi.org/10.1080/13546781003630117

Del Missier, Fabio, Mäntylä, T., & Bruine de Bruin, W. (2012). Decision-making competence, executive functioning, and general cognitive abilities. *Journal of Behavioral Decision*

Making, *25*(4), 331–351. https://doi.org/10.1002/bdm.731

Dilchert, S. (2018). Cognitive ability. In D. S. Ones, N. Anderson, C. Viswesvaran, & H. K. Sinangil (Eds.), *The SAGE Handbook of Industrial, Organizational, and Work Psychology* (2nd ed., Vol. 1, pp. 248–276). SAGE Publications.

Edwards, J. R. (2001). Multidimensional constructs in organizational behavior research: An integrative analytical framework. *Organizational Research Methods*, *4*(2), 144–192. https://doi.org/10.1177/109442810142004

Efron, B., & Tibshirani, R. J. (1994). *An introduction to the bootstrap*. CRC Press.

Everett, C. (2019). *Numbers and the making of us: Counting and the course of human cultures.* Cambridge, MA: Harvard University Press.

Fischhoff, B., Slovic, P., Lichtenstein, S., Read, S., & Combs, B. (1978). How safe is safe enough? A psychometric study of attitudes towards technological risks and benefits. *Policy Sciences*, *9*(2), 127–152. https://doi.org/10.1007/BF00143739

Fong, G. T., Krantz, D. H., & Nisbett, R. E. (1986). The effects of statistical training on thinking about everyday problems. *Cognitive Psychology, 18*(3), 253-292.

Fong, G. T., & Nisbett, R. E. (1991). Immediate and delayed transfer of training effects in statistical reasoning. *Journal of Experimental Psychology: General, 120*(1), 34.

Frederick, S. (2005). Cognitive reflection and decision making. *Journal of Economic Perspectives*, *19*(4), 25–42. https://doi.org/10.1257/089533005775196732

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, *114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Fugas, C. S., Meliá, J. L., & Silva, S. A. (2011). The “ is” and the “ ought”: How do perceived social norms influence safety behaviors at work? *Journal of Occupational Health Psychology*, *16*(1), 67–79. http://doi.org/10.1037/a0021731

Gamliel, E., & Kreiner, H. (2017). Outcome proportions, numeracy, and attribute-framing bias. *Australian Journal of Psychology*, *69*(4), 283–292. https://doi.org/10.1111/ajpy.12151

Gamliel, E., Kreiner, H., & Garcia-Retamero, R. (2016). The moderating role of objective and subjective numeracy in attribute framing. *International Journal of Psychology*, *51*(2), 109–116. https://doi.org/10.1002/ijop.12138

Garcia-Retamero, R., & Cokely, E. T. (2017). Designing visual aids that promote risk literacy: A systematic review of health research and evidence-based design heuristics. *Human Factors*, *59*(4), 582–627.

Garcia-Retamero, R., Sobkow, A., Petrova, D., Garrido, D., & Traczyk, J. (2019). Numeracy and risk literacy: What have we learned so far? *The Spanish Journal of Psychology*, *22*(e10), 1–11. https://doi.org/10.1017/sjp.2019.16

Geiger, V., Goos, M., & Forgasz, H. (2015). A rich interpretation of numeracy for the 21st century: A survey of the state of the field. *ZDM, 47*(4), 531-548.

Ghazal, S., Cokely, E. T., & Garcia-Retamero, R. (2014). Predicting biases in very highly educated samples: Numeracy and metacognition. *Judgment and Decision Making*, *9*(1), 15–34.

Gigerenzer, G. (1996). On narrow norms and vague heuristics: A reply to Kahneman and Tversky. *Psychological Review*, *103*(3), 592–596.

Gigerenzer, G. (2008). Why heuristics work. *Perspectives on Psychological Science*, *3*(1), 20–29. https://doi.org/10.1111/j.1745-6916.2008.00058.x

Gigerenzer, G. (2015). *Risk savvy: How to make good decisions.* New York, NY: Penguin.

Gignac, G. E., & Zajenkowski, M. (2020). The Dunning-Kruger effect is (mostly) a statistical artefact: Valid approaches to testing the hypothesis with individual differences data. *Intelligence*, *80*, 101449. https://doi.org/10.1016/j.intell.2020.101449

Gottfredson, L. S. (1997). Why *g* matters: The complexity of everyday life. *Intelligence*, *24*(1), 79–132. https://doi.org/10.1016/S0160-2896(97)90014-3

Griffin, M. A., Neal, A., & Parker, S. K. (2007). A new model of work role performance: Positive behavior in uncertain and interdependent contexts. *Academy of Management Journal*, *50*(2), 327–347. https://doi.org/10.5465/amj.2007.24634438

Griffin, P., McGaw, B., & Care, E. (Eds.). (2012). *Assessment and teaching of 21st century skills*. Springer Netherlands. https://doi.org/10.1007/978-94-007-2324-5

Grotlüschen, A., Buddeberg, K., Redmer, A., Ansen, H., & Dannath, J. (2019). Vulnerable subgroups and numeracy practices: How poverty, debt, and unemployment relate to everyday numeracy practices. *Adult Education Quarterly*, *69*(4), 251–270. https://doi.org/10.1177/0741713619841132

Gustafsson, J.-E. (1984). A unifying model for the structure of intellectual abilities. *Intelligence*, *8*(3), 179–203. https://doi.org/10.1016/0160-2896(84)90008-4

Hammer, T. H., Saksvik, P. Ø., Nytrø, K., Torvatn, H., & Bayazit, M. (2004). Expanding the psychosocial work environment: Workplace norms and work-family conflict as correlates of stress and health. *Journal of Occupational Health Psychology*, *9*(1), 83–97. https://doi.org/10.1037/1076-8998.9.1.83

Hicks, K. L., Harrison, T. L., & Engle, R. W. (2015). Wonderlic, working memory capacity, and fluid intelligence. *Intelligence*, *50*, 186–195. https://doi.org/10.1016/j.intell.2015.03.005

Highhouse, S., Nye, C. D., Zhang, D. C., & Rada, T. B. (2017). Structure of the DOSPERT: Is there evidence for a general risk factor? *Journal of Behavioral Decision Making*, *30*(2), 400–406. https://doi.org/10.1002/bdm.1953

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

Hunt, E. (2010). *Human intelligence.* Cambridge University Press.

Hunter, J. E. (1986). Cognitive ability, cognitive aptitudes, job knowledge, and job performance. *Journal of Vocational Behavior*, *29*(3), 340–362. https://doi.org/10.1016/0001-8791(86)90013-8

Jensen, A. R. (1998). *The g factor: The science of mental ability*. Praeger.

Johnson, J. W. (2000). A heuristic method for estimating the relative weight of predictor variables in multiple regression. *Multivariate Behavioral Research*, *35*(1), 1–19. https://doi.org/10.1207/S15327906MBR3501_1

Johnson, J. W., & Carter, G. W. (2010). Validating synthetic validation: Comparing traditional and synthetic validity coefficients. *Personnel Psychology*, *63*(3), 755–795. https://doi.org/10.1111/j.1744-6570.2010.01186.x

Johnson, J. W., & LeBreton, J. M. (2004). History and use of relative importance indices in organizational research. *Organizational Research Methods*, *7*(3), 238–257. https://doi.org/10.1177/1094428104266510

Jung, R. E., & Haier, R. J. (2007). The parieto-frontal integration theory (P-FIT) of intelligence: Converging neuroimaging evidence. *Behavioral and Brain Sciences*, *30*(2), 135–154. https://doi.org/10.1017/S0140525X07001185

Kahneman, D. (2013). *Thinking, fast and slow*. Farrar, Straus and Giroux.

Kahneman, D., & Klein, G. (2009). Conditions for intuitive expertise: a failure to disagree. *American Psychologist, 64*(6), 515–526. https://doi.org/10.1037/a0016755

Keogh, J. J., Maguire, T., & O'Donoghue, J. (2014). A workplace contextualisation of mathematics: Measuring workplace context complexity. *Adults Learning Mathematics*, *9*(1), 85–99.

Kirsch, I. S., Jungeblut, A., Jenkins, L., & Kolstad, A. (1993). *Adult literacy in America: A first look at the results of the National Adult Literacy Survey*. Educational Testing Service. https://eric.ed.gov/?id=ED358375

Lai, K., & Green, S. B. (2016). The problem with having two watches: Assessment of fit when RMSEA and CFI disagree. *Multivariate Behavioral Research*, *51*(2–3), 220–239. https://doi.org/10.1080/00273171.2015.1134306

Lake, C. J., & Highhouse, S. (2013). Assessing decision-making competence in managers. In S. Highhouse, R. S. Dalal, & E. Salas (Eds.), *Judgment and Decision Making at Work* (pp. 326–351). New York, NY: Routledge.

Lang, J. W. B., & Kell, H. J. (2019). General mental ability and specific abilities: Their relative importance for extrinsic career success. *Journal of Applied Psychology*. https://doi.org/10.1037/apl0000472

Lang, J. W. B., Kersting, M., Hülsheger, U. R., & Lang, J. (2010). General mental ability, narrower cognitive abilities, and job performance: The perspective of the nested-factors model of cognitive abilities. *Personnel Psychology*, *63*(3), 595–640. https://doi.org/10.1111/j.1744-6570.2010.01182.x

Larson, E. C. (2019). *A meta-analysis of information processing measures of intelligence, performance, and group score differences* (Doctoral dissertation). City University of New

York.

LeBreton, J. M., Hargis, M. B., Griepentrog, B., Oswald, F. L., & Ployhart, R. E. (2007). A multidimensional approach for evaluating variables in organizational research and practice. *Personnel Psychology*, *60*(2), 475–498. https://doi.org/10.1111/j.1744-6570.2007.00080.x

LeBreton, J. M., Ployhart, R. E., & Ladd, R. T. (2004). A Monte Carlo comparison of relative importance methodologies. *Organizational Research Methods*, *7*(3), 258–282. https://doi.org/10.1177/1094428104266017

Lerner, J. S., & Tetlock, P. E. (1999). Accounting for the effects of accountability. *Psychological Bulletin*, *125*(2), 255–275. https://doi.org/10.1037/0033-2909.125.2.255

Liberali, J. M., Reyna, V. F., Furlan, S., Stein, L. M., & Pardo, S. T. (2012). Individual differences in numeracy and cognitive reflection, with implications for biases and fallacies in probability judgment. *Journal of Behavioral Decision Making*, *25*(4), 361–381. https://doi.org/10.1002/bdm.752

Little, T. D., Cunningham, W. A., Shahar, G., & Widaman, K. F. (2002). To parcel or not to parcel: Exploring the question, weighing the merits. *Structural Equation Modeling*, *9*(2), 151–173. https://doi.org/10.1207/S15328007SEM0902_1

Loehlin, J. C., & Beaujean, A. A. (2017). *Latent variable models: An introduction to factor, path, and structural equation analysis* (5th ed.). Routledge.

Lovallo, D., & Kahneman, D. (2003). Delusions of success. How optimism undermines executives' decisions. *Harvard Business Review*, *81*(7), 56–63, 117.

Mata, R., Pachur, T., von Helversen, B., Hertwig, R., Rieskamp, J., & Schooler, L. (2012). Ecological rationality: A framework for understanding and aiding the aging decision maker. *Frontiers in Neuroscience*, *6*, 19. https://doi.org/10.3389/fnins.2012.00019

Matthews, T. D., & Lassiter, K. S. (2007). What does the Wonderlic Personnel Test measure? *Psychological Reports*, *100*(3), 707–712. https://doi.org/10.2466/pr0.100.3.707-712

Meade, A. W., & Bauer, D. J. (2007). Power and precision in confirmatory factor analytic tests of measurement invariance. *Structural Equation Modeling: A Multidisciplinary Journal*, *14*(4), 611–635. https://doi.org/10.1080/10705510701575461

Meikle, N. L., Tenney, E. R., & Moore, D. A. (2016). Overconfidence at work: Does overconfidence survive the checks and balances of organizational life? *Research in Organizational Behavior*, *36*, 121–134. https://doi.org/10.1016/j.riob.2016.11.005

Melby-Lervåg, M., Redick, T. S., & Hulme, C. (2016). Working memory training does not improve performance on measures of intelligence or other measures of "far transfer": evidence from a meta-analytic review. *Perspectives on Psychological Science*, *11*(4), 512–534. https://doi.org/10.1177/1745691616635612

Ministry of Education. (1959). *15 to 18: A report of the Central Advisory Committee for Education* (England). London: Department of Education and Science.

Moore, D. A., & Healy, P. J. (2008). The trouble with overconfidence. *Psychological Review*, *115*(2), 502–517. https://doi.org/10.1037/0033-295X.115.2.502

Mumford, M. D., Connelly, S., Brown, R. P., Murphy, S. T., Hill, J. H., Antes, A. L., Waples, E. P., & Devenport, L. D. (2008). A sensemaking approach to ethics training for scientists: Preliminary evidence of training effectiveness. *Ethics & Behavior*, *18*(4), 315–339. https://doi.org/10.1080/10508420802487815

Murphy, K. R., & Shiarella, A. H. (1997). Implications of the multidimensional nature of job performance for selection tests: Multivariate framework for studying test validity.

Personnel Psychology, *50*(4), 823–854. https://doi.org/10.1111/j.1744-6570.1997.tb01484.x

Nathans, L. L., Oswald, F. L., & Nimon, K. (2012). Interpreting multiple linear regression: A guidebook of variable importance. *Practical Assessment, Research & Evaluation*, *17*, 9.

Neisser, U., Boodoo, G., Bouchard, T. J., Boykin, A. W., Brody, N., Ceci, S. J., ... & Urbina, S. (1996). Intelligence: knowns and unknowns. *American Psychologist, 51*(2), 77–101.

Nimon, K. F., & Oswald, F. L. (2013). Understanding the results of multiple linear regression: Beyond standardized regression coefficients. *Organizational Research Methods*, *16*(4), 650–674. https://doi.org/10.1177/1094428113493929

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

Parker, A. M., Bruine de Bruin, W., Fischhoff, B., & Weller, J. (2017). Robustness of decision-making competence: Evidence from two measures and an 11-year longitudinal study. *Journal of Behavioral Decision Making*. https://doi.org/10.1002/bdm.2059

Parker, A. M., & Fischhoff, B. (2005). Decision-making competence: External validation through an individual-differences approach. *Journal of Behavioral Decision Making*, *18*(1), 1–27. https://doi.org/10.1002/bdm.481

Patel, N. (2017). *The cognitive reflection test: A measure of intuition/reflection, numeracy, and insight problem solving, and the implications for understanding real-world judgments and beliefs* (Doctoral dissertation). University of Missouri–Columbia.

Paulos, J. A. (1988). *Innumeracy: Mathematical illiteracy and its consequences*. Hill and Wang.

Peters, E. (2012). Beyond comprehension: The role of numeracy in judgments and decisions. *Current Directions in Psychological Science*, *21*(1), 31–35. https://doi.org/10.1177/0963721411429960

Peters, E., & Bjalkebring, P. (2015). Multiple numeric competencies: When a number is not just a number. *Journal of Personality and Social Psychology*, *108*(5), 802–822. https://doi.org/10.1037/pspp0000019

Peters, E., & Levin, I. P. (2008). Dissecting the risky-choice framing effect: Numeracy as an individual-difference factor in weighting risky and riskless options. *Judgment and Decision Making*, *3*(6), 435–448.

Peters, E., Västfjäll, D., Slovic, P., Mertz, C. K., Mazzocco, K., & Dickert, S. (2006). Numeracy and decision making. *Psychological Science*, *17*(5), 407–413. https://doi.org/10.1111/j.1467-9280.2006.01720.x

Postlethwaite, B. E. (2011). *Fluid ability, crystallized ability, and performance across multiple domains: A meta-analysis* (Doctoral dissertation). The University of Iowa.

Potworowski, G. A. (2010). *Varieties of indecisive experience: Explaining the tendency to not make timely and stable decisions* (Doctoral dissertation). University of Michigan.

Pronin, E., Lin, D. Y., & Ross, L. (2002). The Bias Blind Spot: Perceptions of Bias in Self Versus Others. *Personality and Social Psychology Bulletin*, *28*(3), 369–381. https://doi.org/10.1177/0146167202286008

Raven, J. C. (1936). *Mental tests used in genetic studies: The performance of related individuals on tests mainly educative and mainly reproductive* (Master's thesis). University of London.

Redmer, A., & Dannath, J. (2019). Changes in employment since the 1990s: Numeracy practices at work in IALS and PIAAC. *ZDM*. https://doi.org/10.1007/s11858-019-01112-1

Ree, M. J., & Earles, J. A. (1991). Predicting training success: Not much more than g. *Personnel Psychology*, *44*(2), 321–332. https://doi.org/10.1111/j.1744-6570.1991.tb00961.x

Ree, M. J., Earles, J. A., & Teachout, M. S. (1994). Predicting job performance: Not much more than g. *Journal of Applied Psychology*, *79*(4), 518–524. https://doi.org/10.1037/0021-9010.79.4.518

Reyna, V. F., Nelson, W. L., Han, P. K., & Dieckmann, N. F. (2009). How numeracy influences risk comprehension and medical decision making. *Psychological Bulletin*, *135*(6), 943–973. https://doi.org/10.1037/a0017327

Rosi, A., Bruine de Bruin, W., Del Missier, F., Cavallini, E., & Russo, R. (2019). Decision-making competence in younger and older adults: Which cognitive abilities contribute to the application of decision rules? *Aging, Neuropsychology, and Cognition*, *26*(2), 174–189. https://doi.org/10.1080/13825585.2017.1418283

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. *Journal of Statistical Software*, *48*(2), 1–36.

Roth, S., Robbert, T., & Straus, L. (2015). On the sunk-cost effect in economic decision-making: A meta-analytic review. *Business Research*, *8*(1), 99–138. https://doi.org/10.1007/s40685-014-0014-8

Sackett, P. R., Lievens, F., Van Iddekinge, C. H., & Kuncel, N. R. (2017). Individual differences and their measurement: A review of 100 years of research. *Journal of Applied Psychology*, *102*(3), 254–273. https://doi.org/10.1037/apl0000151

Sala, G., Aksayli, N. D., Tatlidil, K. S., Tatsumi, T., Gondo, Y., & Gobet, F. (2019). Near and far transfer in cognitive training: A second-order meta-analysis. *Collabra: Psychology, 5*(1).

Sala, G., & Gobet, F. (2017). Does far transfer exist? Negative evidence from chess, music, and working memory training. *Current Directions in Psychological Science, 26*(6), 515-520.

Scherbaum, C. A. (2005). Synthetic validity: Past, present, and future. *Personnel Psychology*, *58*(2), 481–515. https://doi.org/10.1111/j.1744-6570.2005.00547.x

Scherbaum, C. A., Goldstein, H. W., Yusko, K. P., Ryan, R., & Hanges, P. J. (2012). Intelligence 2.0: Reestablishing a Research Program on g in I–O Psychology. *Industrial and Organizational Psychology*, *5*(2), 128–148. https://doi.org/10.1111/j.1754-9434.2012.01419.x

Schmidt, F. L., & Hunter, J. E. (1998). The validity and utility of selection methods in personnel psychology: Practical and theoretical implications of 85 years of research findings. *Psychological Bulletin*, *124*(2), 262–274. https://doi.org/10.1037/0033-2909.124.2.262

Schmidt, F. L., & Hunter, J. E. (2014). *Methods of meta-analysis: Correcting error and bias in research findings* (3rd ed.). SAGE Publications.

Schwartz, L. M., Woloshin, S., Black, W. C., & Welch, H. G. (1997). The role of numeracy in understanding the benefit of screening mammography. *Annals of Internal Medicine*, *127*(11), 966. https://doi.org/10.7326/0003-4819-127-11-199712010-00003

Shaffer, J. A., DeGeest, D., & Li, A. (2016). Tackling the problem of construct proliferation: A guide to assessing the discriminant validity of conceptually related constructs. *Organizational Research Methods*, *19*(1), 80–110. https://doi.org/10.1177/1094428115598239

Shore, B. (2008). Systematic biases and culture in project failures. *Project Management Journal*, *39*(4), 5–16. https://doi.org/10.1002/pmj.20082

Simon, A. F., Fagley, N. S., & Halleran, J. G. (2004). Decision framing: Moderating effects of individual differences and cognitive processing. Journal of Behavioral Decision Making, 17(2), 77-93.

Simons, D. J., Boot, W. R., Charness, N., Gathercole, S. E., Chabris, C. F., Hambrick, D. Z., &

Stine-Morrow, E. A. (2016). Do “brain-training” programs work?. *Psychological Science in the Public Interest, 17*(3), 103-186.

Snyder, M. (1974). Self-monitoring of expressive behavior. *Journal of Personality and Social Psychology*, *30*(4), 526–537. http://dx.doi.org.ezproxy.lib.ou.edu/10.1037/h0037039

Sobkow, A., Olszewska, A., & Traczyk, J. (2020). Multiple numeric competencies predict decision outcomes beyond fluid intelligence and cognitive reflection. *Intelligence*, *80*, 101452. https://doi.org/10.1016/j.intell.2020.101452

Spearman, C. (1904). “General intelligence,” objectively determined and measured. *The American Journal of Psychology*, *15*(2), 201–292. https://doi.org/10.2307/1412107

Stanovich, K. E. (2009). *What intelligence tests miss: The psychology of rational thought*. Yale University Press.

Stanovich, K. E., & West, R. F. (1998). Individual differences in framing and conjunction effects. *Thinking & Reasoning, 4*(4), 289-317.

Stanovich, K. E., West, R. F., & Toplak, M. E. (2016). *The rationality quotient: Toward a test of rational thinking*. Cambridge, MA: MIT Press.

Strough, J., Bruine de Bruin, W., Parker, A. M., Karns, T., Lemaster, P., Pichayayothin, N., Delaney, R., & Stoiko, R. (2016). What Were They Thinking? Reducing Sunk-Cost Bias in a Life-Span Sample. *Psychology and Aging*, *31*(7), 724–736. https://doi.org/10.1037/pag0000130

Sylves, R. T., & Comfort, L. K. (2012). The Exxon Valdez and BP Deepwater Horizon Oil Spills: Reducing Risk in Socio-Technical Systems. *American Behavioral Scientist*, *56*(1), 76–103. https://doi.org/10.1177/0002764211413116

Teovanović, P., Knežević, G., & Stankov, L. (2015). Individual differences in cognitive biases:

Evidence against one-factor theory of rationality. *Intelligence*, *50*, 75–86. https://doi.org/10.1016/j.intell.2015.02.008

Tillman, F. A., & Cassone, D. T. (2012). *A Professional's Guide to Decision Science and Problem Solving: An Integrated Approach for Assessing Issues, Finding Solutions, and Reaching Corporate Objectives.* FT Press.

Tout, D., Coben, D., Geiger, V., Ginsburg, L., Hoogland, K., Maguire, T., Thomson, S., & Turner, R. (2017). *Review of the PIAAC numeracy assessment framework: Final report* (p. 64). Australian Council for Educational Research.

Van Iddekinge, C. H., & Ployhart, R. E. (2008). Developments in the criterion-related validation of selection procedures: A critical review and recommendations for practice. *Personnel Psychology*, *61*(4), 871–925.

Vancouver, J. B., & Kendall, L. N. (2006). When self-efficacy negatively relates to motivation and performance in a learning context. *Journal of Applied Psychology*, *91*(5), 1146–1153. https://doi.org/10.1037/0021-9010.91.5.1146

Werner, M. D., & Cornelissen, J. P. (2014). Framing the change: Switching and blending frames and their role in instigating institutional change. *Organization Studies*, *35*(10), 1449–1472. https://doi.org/10.1177/0170840614539314

West, R. F., Meserve, R. J., & Stanovich, K. E. (2012). Cognitive sophistication does not attenuate the bias blind spot. *Journal of Personality and Social Psychology*, *103*(3), 506–519. http://dx.doi.org.ezproxy.lib.ou.edu/10.1037/a0028857

Wille, B., & De Fruyt, F. (2014). Vocations as a source of identity: Reciprocal relations between Big Five personality traits and RIASEC characteristics over 15 years. *Journal of Applied Psychology*, *99*(2), 262–281. http://dx.doi.org.ezproxy.lib.ou.edu/10.1037/a0034917

Wonderlic, E. F. (2007). *Wonderlic Personnel Test-Revised: Manual*. Western Psychological Services.

Wonderlic, E. F., & Hovland, C. I. (1939). The personnel test: A restandardized abridgment of the Otis S-A test for business and industrial use. *Journal of Applied Psychology*, *23*(6), 685–702. https://doi.org/10.1037/h0056432

Woods, J. A. (2015). *Dominant logic, decision-making heuristics, and selective information processing as antecedents to financial escalation of commitment in small family firms* (Doctoral dissertation). University of Cincinnati.

Xia, N., Wang, X., Griffin, M. A., Wu, C., & Liu, B. (2017). Do we see how they perceive risk? An integrated analysis of risk perception and its effect on workplace safety behavior. *Accident Analysis & Prevention*, *106*, 234–242. https://doi.org/10.1016/j.aap.2017.06.010

Yates, J. F. (2003). *Decision management: How to assure better decisions in your company* (1st ed.). Jossey-Bass.

Yates, J. F., & Tschirhart, M. D. (2006). Decision-making expertise. In K. A. Ericsson, N. Charness, P. J. Feltovich, & R. R. Hoffman (Eds.), *The Cambridge Handbook of Expertise and Expert Performance* (pp. 421–438). Cambridge University Press. https://doi.org/10.1017/CBO9780511816796.024

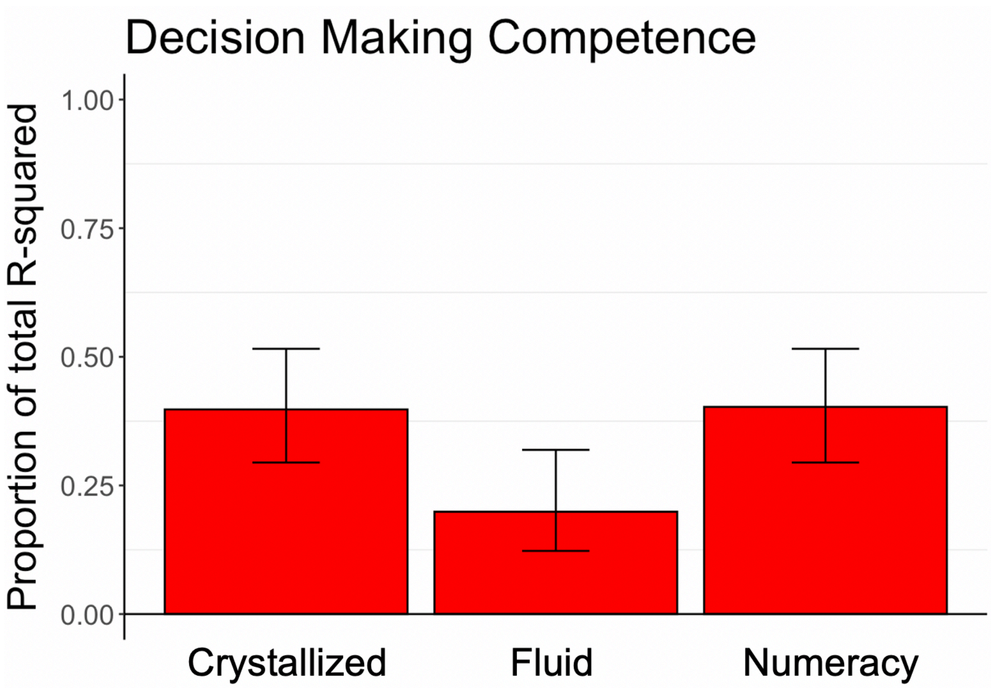
Zhang, D. C., & Highhouse, S. (2018). Judgment and decision making in the workplace. In D. S. Ones, N. R. Anderson, C. Viswesvaran, & H. K. Sinangil (Eds.), *The SAGE handbook of industrial, work & organizational psychology* (pp. 611–633). Sage.

Zhang, P., Lingard, H., Blismas, N., Wakefield, R., & Kleiner, B. (2015). Work-health and safety-risk perceptions of construction-industry stsakeholders using photograph-based Q methodology. *Journal of Construction Engineering and Management*, *141*(5), 04014093.

https://doi.org/10.1061/(ASCE)CO.1943-7862.0000954

Figures

Figure 1. *General dominance weights for decision-making competence*



Note. Error bars are 95% confidence intervals.

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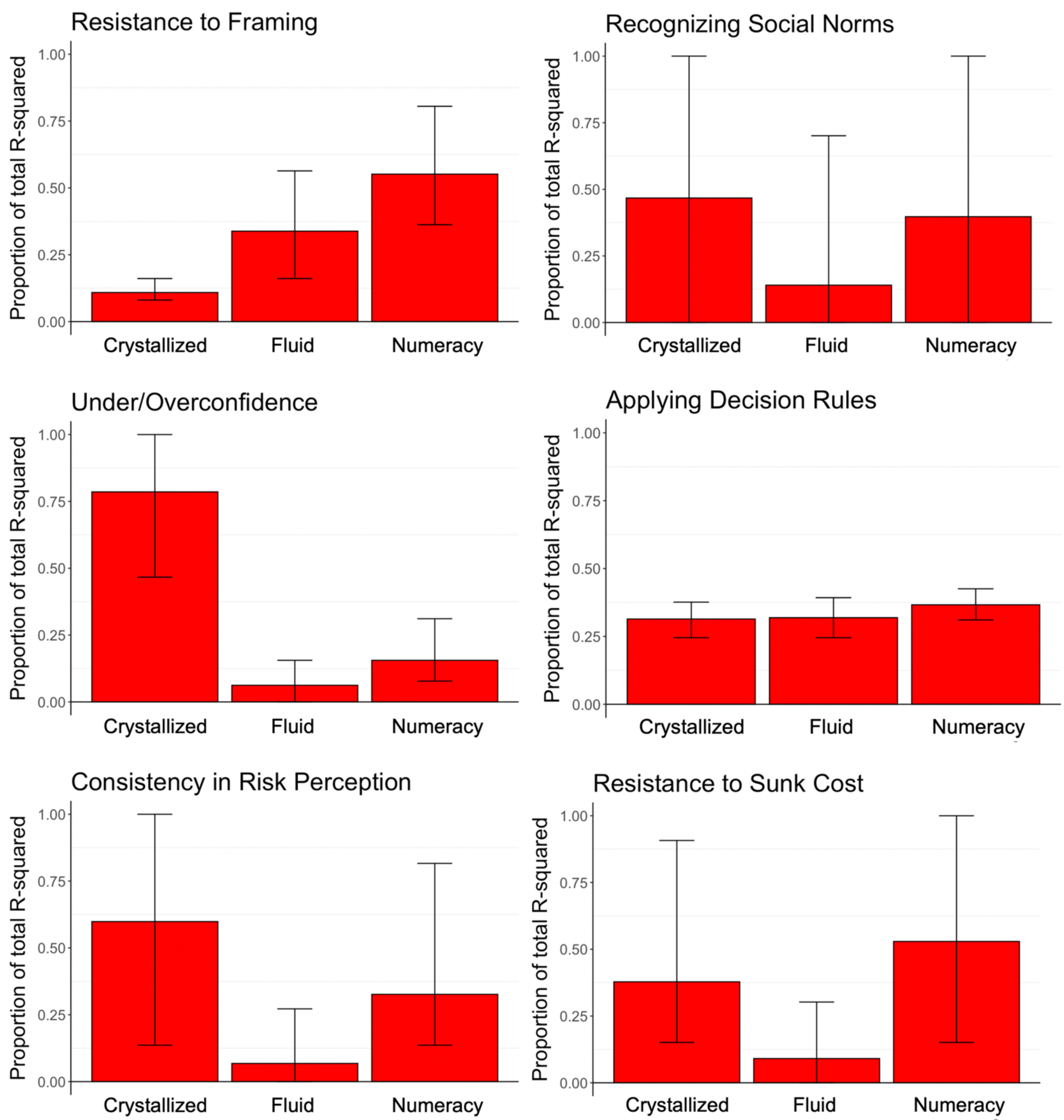
Figure 2. *General dominance weights for each dimension of decision-making competence*



Note. Error bars are 95% confidence intervals.

Tables

Table 1. *Descriptive Statistics*

	α	Mean	*SD*	Min	Max	Skew	Kurtosis
Crystallized ability	.73	24.2	4.99	1.00	38.00	–0.19	0.11
Fluid ability	.75	6.23	2.77	0.00	12.00	–0.07	–0.46
Numeracy	.61	3.32	1.62	0.00	7.00	0.40	–0.36
Decision-making competence	.79	0.00	0.52	–2.18	1.27	–0.56	0.88
Resistance to Framing	.53	4.05	0.39	2.43	5.00	–0.51	0.61
Recognizing Social Norms	.74	0.44	0.22	–0.37	0.88	–0.90	1.23
Under/Overconfidence	.76	0.73	0.07	0.43	0.92	–0.29	0.68
Applying Decision Rules	.71	0.51	0.22	0.00	0.91	–0.26	–0.76
Consistency in Risk Perception	.76	0.78	0.15	0.00	1.00	–1.24	2.26
Resistance to Sunk Cost	.39	4.07	0.66	1.80	6.00	0.14	0.26

Note. Decision-making competence is the unit-weighted average of standardized scores on the six A-DMC subscales. Cronbach's alpha for Recognizing Social Norms is the average of the reliability coefficients for self and peer ratings (Bruine de Bruin et al., 2007). Cronbach's alpha for Under/Overconfidence was calculated using 14 indicators representing the self-reported confidence-weighted response to each dichotomous item.

Table 2. *Correlations Among the Study Variables*

	1	2	3	4	5	6	7	8	9	10
1. Crystallized ability	**.73**	.50	.68	.57	.25	.19	.36	.66	.26	.22
2. Fluid ability	.37	**.75**	.60	.46	.40	.13	.15	.65	.12	.13
3. Numeracy	.46	.41	**.61**	.58	.46	.19	.21	.70	.22	.24
4. Decision Making Competence	.44	.35	.41	**.79**	.71	.68	.65	.83	.68	.85
5. Resistance to Framing	.16	.25	.26	.46	**.53**	.27	–.09	.38	.09	.10
6. Recognizing Social Norms	.14	.09	.12	.52	.17	**.74**	.17	.17	.10	.20
7. Under/Overconfidence	.26	.11	.14	.51	–.06	.13	**.76**	.32	.21	.18
8. Applying Decision Rules	.47	.47	.46	.62	.23	.12	.23	**.71**	.30	.22
9. Consistency in Risk Perception	.20	.09	.15	.53	.06	.07	.16	.22	**.76**	.19
10. Resistance to Sunk Cost	.12	.07	.12	.47	.04	.11	.10	.12	.11	**.39**

Note. Diagonals are reliability coefficients. Observed correlations are below the diagonal and correlations corrected for measurement error are above the diagonal. $r > |.10| = p < .05$; $r > |.14| = p < .01$; $r > |.18| = p < .05$.

Table 3. *Fit Statistics for Measurement Invariance of Crystallized Ability Across Gender*

Model	χ^2	*df*	CFI	RMSEA	95% CI	SRMR	AIC	Model Comparison	
								$\Delta\chi^2$	Δdf
Baseline	64.666	35	.942	.049	(.030, .067)	.041	-2291.20		
Configural	106.736	70	.929	.054	(.032, .074)	.050	-2291.50	42.070	35
Metric	122.514	79	.916	.056	(.035, .074)	.065	-2293.70	15.778	9
Scalar	148.985	88	.882	.062	(.045, .079)	.071	-2285.30	26.471**	9
Strict	159.112	98	.881	.059	(.042, .076)	.075	-2295.10	10.127	10

Note. df = degrees of freedom; CFI = Comparative Fit Index, RMSEA = Root Mean Square of Approximation; SRMR = Standardized Root Mean Square Residual; AIC = Akaike Information Criterion.

Table 4. *Fit Statistics for Measurement Invariance of Fluid Ability Across Gender*

Model	χ^2	*df*	CFI	RMSEA	95% CI	SRMR	AIC	Model Comparison	
								$\Delta\chi^2$	Δdf
Baseline	135.394	54	.857	.065	(.052, .079)	.052	4653.9		
Configural	180.884	108	.874	.062	(.046, .077)	.060	4679.0	45.490	54
Metric	203.677	119	.854	.063	(.048, .078)	.073	4679.8	22.793**	11
Scalar	215.432	130	.852	.061	(.046, .075)	.075	4669.6	11.755	11
Strict	225.745	142	.855	.058	(.043, .071)	.074	4655.9	10.313	12

Note. df = degrees of freedom; CFI = Comparative Fit Index, RMSEA = Root Mean Square of Approximation; SRMR = Standardized Root Mean Square Residual; AIC = Akaike Information Criterion.

Table 5. *Fit Statistics for Measurement Invariance of Numeracy Across Gender*

Model	χ^2	*df*	CFI	RMSEA	95% CI	SRMR	AIC	Model Comparison $\Delta\chi^2$	Δdf
Baseline	18.981	14	.977	.032	(.000, .064)	.033	2492.7		
Configural	33.753	28	.969	.034	(.000, .070)	.044	2413.4	14.772	14
Metric	34.808	34	.996	.012	(.000, .056)	.046	2402.5	1.056	6
Scalar	54.194	40	.922	.045	(.000, .073)	.061	2409.9	19.385**	6
Strict	117.120	47	.617	.092	(.071, .113)	.118	2458.8	62.927***	7

Note. df = degrees of freedom; CFI = Comparative Fit Index, RMSEA = Root Mean Square of Approximation; SRMR = Standardized Root Mean Square Residual; AIC = Akaike Information Criterion.

Table 6. *Fit Statistics for Measurement Invariance of Decision-Making Competence Across Gender*

Model	χ^2	*df*	CFI	RMSEA	95% CI	SRMR	AIC	Model Comparison $\Delta\chi^2$	Δdf
Baseline	21.474	9	.843	.063	(.029, .098)	.040	5865.2		
Configural	24.975	18	.906	.047	(.000, .088)	.043	5880.5	3.501	9
Metric	34.001	23	.852	.052	(.000, .087)	.055	5879.6	9.025	5
Scalar	37.891	28	.867	.045	(.000, .078)	.059	5873.4	3.891	5
Strict	38.384	34	.941	.027	(.000, .063)	.060	5861.9	0.493	6

Note. df = degrees of freedom; CFI = Comparative Fit Index, RMSEA = Root Mean Square of Approximation; SRMR = Standardized Root Mean Square Residual; AIC = Akaike Information Criterion.

Table 7. *Fit Statistics for Measurement Invariance of Resistance to Framing Across Gender*

Model	χ^2	*df*	CFI	RMSEA	95% CI	SRMR	AIC	Model Comparison	
								$\Delta\chi^2$	Δdf
Baseline	137.765	77	.588	.049	(.035, .062)	.055	13360.9		
Configural	270.087	154	.460	.067	(.054, .080)	.075	13369.5	132.32***	77
Metric	299.360	167	.385	.069	(.056, .081)	.082	13372.8	29.273**	13
Scalar	318.843	180	.355	.068	(.056, .080)	.085	13366.3	19.483	13
Strict	339.166	194	.325	.067	(.055, .079)	.090	13358.6	20.323	14

Note. df = degrees of freedom; CFI = Comparative Fit Index, RMSEA = Root Mean Square of Approximation; SRMR = Standardized Root Mean Square Residual; AIC = Akaike Information Criterion.

Table 8. *Fit Statistics for Measurement Invariance of Under/Overconfidence Across Gender*

Model	χ^2	*df*	CFI	RMSEA	95% CI	SRMR	AIC	Model Comparison	
								$\Delta\chi^2$	Δdf
Baseline	783.849	527	.720	.038	(.032, .044)	.055	-4163.7		
Configural	1464.09	1054	.632	.048	(.042, .054)	.073	-4220.9	680.240***	527
Metric	1546.27	1087	.588	.050	(.044, .056)	.083	-4204.8	82.175***	33
Scalar	1636.22	1120	.537	.053	(.047, .058)	.085	-4180.8	89.950***	33
Strict	1721.47	1154	.491	.054	(.049, .060)	.090	-4163.6	85.255***	34

Note. df = degrees of freedom; CFI = Comparative Fit Index, RMSEA = Root Mean Square of Approximation; SRMR = Standardized Root Mean Square Residual; AIC = Akaike Information Criterion.

Table 9. *Fit Statistics for Measurement Invariance of Applying Decision Rules Across Gender*

Model	χ^2	*df*	CFI	RMSEA	95% CI	SRMR	AIC	Model Comparison $\Delta\chi^2$	Δdf
Baseline	48.595	35	.964	.033	(.000, .054)	.038	4183.7		
Configural	86.094	70	.956	.036	(.000, .059)	.048	4210.1	37.500	35
Metric	89.300	79	.972	.027	(.000, .052)	.052	4195.3	3.205	9
Scalar	101.428	88	.963	.029	(.000, .052)	.056	4189.4	12.129	9
Strict	114.580	98	.955	.031	(.000, .052)	.064	4182.5	13.152	10

Note. df = degrees of freedom; CFI = Comparative Fit Index, RMSEA = Root Mean Square of Approximation; SRMR = Standardized Root Mean Square Residual; AIC = Akaike Information Criterion.

Table 10. *Fit Statistics for Measurement Invariance of Consistency in Risk Perception across Gender*

Model	χ^2	*df*	CFI	RMSEA	95% CI	SRMR	AIC	Model Comparison $\Delta\chi^2$	Δdf
Baseline	687.030	135	.524	.107	(.099, .115)	.091	4026.2		
Configural	951.650	270	.475	.119	(.111, .128)	.103	4079.6	264.62***	135
Metric	971.619	287	.472	.116	(.108, .124)	.106	4065.5	19.969	17
Scalar	982.827	304	.477	.112	(.104, .120)	.106	4042.8	11.208	17
Strict	1003.600	322	.475	.109	(.102, .117)	.108	4027.5	20.773	18

Note. df = degrees of freedom; CFI = Comparative Fit Index, RMSEA = Root Mean Square of Approximation; SRMR = Standardized Root Mean Square Residual; AIC = Akaike Information Criterion.

Table 11. *Dominance Analysis of Overall Decision-Making Competence Regressed on the Predictors*

			Additional contribution of:					
	R^2		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.33**	**(.25, .40)**	**.21**	**(.13, .29)**	**.34**	**(.26, .41)**
Crystal	.33	(.25, .40)			.04	(.01, .08)	.07	(.04, .11)
Fluid	.21	(.13, .29)	.16	(.10, .22)			.15	(.09, .22)
Numeracy	.34	(.26, .41)	.06	(.03, .10)	.02	(.00, .05)		
***k* = 1 average**			**.11**	**(.07, .15)**	**.03**	**(.01, .07)**	**.11**	**(.07, .16)**
Crystallized & Fluid	.37	(.28, .44)					.04	(.01, .08)
Crystallized & Numeracy	.40	(.32, .47)			.01	(.00, .04)		
Fluid & Numeracy		(.28, .43)						
	.36		.05	(.02, .09)				
***k* = 2 average**			**.05**	**(.02, .09)**	**.01**	**(.00, .04)**	**.04**	**(.01, .08)**
Crystallized & Fluid & Numeracy	.41	(.33, .48)						
Overall average			**.16**	**(.12, .21)**	**.08**	**(.05, .13)**	**.16**	**(.12, .21)**
% of R^2 explained			40%	(29-52%)	20%	(12-31%)	40%	(29-52%)

Note. Analyses were conducted using correlations corrected for measurement error. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table 12. *Bootstrap Results of Dominance Analysis for Decision-Making Competence*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	1	.982	.109	.969	.006	.025
Crystallized	Numeracy	.5	.480	.442	.371	.411	.218
Fluid	Numeracy	0	.050	.153	.002	.903	.095
Conditional dominance							
Crystallized	Fluid	1	.982	.109	.969	.006	.025
Crystallized	Numeracy	.5	.480	.442	.371	.411	.218
Fluid	Numeracy	0	.050	.153	.002	.903	.095
General dominance							
Crystallized	Fluid	1	.988	.109	.988	.012	.000
Crystallized	Numeracy	0	.461	.499	.461	.539	.000
Fluid	Numeracy	0	.008	.089	.008	.992	.000

Note. Analyses were conducted using correlations corrected for measurement error. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table 13. *Dominance Analysis of Resistance to Framing Regressed on the Predictors*

			Additional contribution of:					
	R^2		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.06**	**(.03, .12)**	**.16**	**(.10, .24)**	**.21**	**(.14, .29)**
Crystal	.06	(.03, .12)			.10	(.05, .17)	.15	(.10, .23)
Fluid	.16	(.10, .24)	.00	(.00, .02)			.08	(.03, .14)
Numeracy	.21	(.14, .29)	.01	(.00, .03)	.02	(.00, .07)		
***k* = 1 average**			**.01**	**(.00, .02)**	**.06**	**(.03, .12)**	**.12**	**(.07, .17)**
Crystallized & Fluid	.16	(.10, .25)					.08	(.04, .14)
Crystallized & Numeracy	.22	(.14, .30)			.03	(.01, .08)		
Fluid & Numeracy	.24	(.16, .32)	.01	(.00, .04)				
***k* = 2 average**			**.01**	**(.00, .04)**	**.03**	**(.01, .08)**	**.08**	**(.04, .14)**
Crystallized & Fluid & Numeracy	.25	(.18, .33)						
Overall average			**.03**	**(.02, .04)**	**.08**	**(.04, .14)**	**.14**	**(.09, .20)**
% of R^2 explained			12%	(7-14%)	32%	(18-56%)	56%	(34-79%)

Note. Analyses were conducted using correlations corrected for measurement error. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table 14. *Bootstrap Results of Dominance Analysis for Resistance to Framing*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	0	.072	.178	.001	.856	.143
Crystallized	Numeracy	0	.000	.000	.000	1.000	.000
Fluid	Numeracy	0	.115	.305	.097	.867	.036
Conditional dominance							
Crystallized	Fluid	0	.072	.178	.001	.856	.143
Crystallized	Numeracy	0	.000	.000	.000	1.000	.000
Fluid	Numeracy	0	.115	.305	.097	.867	.036
General dominance							
Crystallized	Fluid	0	.001	.032	.001	.999	.000
Crystallized	Numeracy	0	.000	.000	.000	1.000	.000
Fluid	Numeracy	0	.112	.316	.112	.888	.000

Note. Analyses were conducted using correlations corrected for measurement error. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table 15. *Dominance Analysis of Recognizing Social Norms Regressed on the Predictors*

			Additional contribution of:					
	R^2		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.04**	**(.01, .09)**	**.02**	**(.00, .05)**	**.03**	**(.01, .08)**
Crystal	.04	(.01, .09)			.00	(.00, .02)	.01	(.00, .03)
Fluid	.02	(.00, .05)	.02	(.00, .06)			.02	(.00, .06)
Numeracy	.03	(.01, .08)	.01	(.00, .04)	.00	(.00, .01)		
***k* = 1 average**			**.02**	**(.00, .05)**	**.00**	**(.00, .01)**	**.01**	**(.00, .04)**
Crystallized & Fluid	.04	(.01, .09)					.00	(.00, .03)
Crystallized & Numeracy	.04	(.01, .10)			.00	(.00, .01)		
Fluid & Numeracy	.03	(.01, .08)	.01	(.00, .04)				
***k* = 2 average**			**.01**	**(.00, .04)**	**.00**	**(.00, .01)**	**.00**	**(.00, .03)**
Crystallized & Fluid & Numeracy	.04	(.01, .10)						
Overall average			**.02**	**(.00, .06)**	**.01**	**(.00, .03)**	**.02**	**(.00, .05)**
% of R^2 explained			47%	(9-100)%	14%	(2-58%)	39%	(9-100%)

Note. Analyses were conducted using correlations corrected for measurement error. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table 16. *Bootstrap Results of Dominance Analysis for Recognizing Social Norms*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	1	.836	.328	.777	.105	.118
Crystallized	Numeracy	1	.559	.484	.534	.415	.051
Fluid	Numeracy	0	.180	.309	.075	.715	.210
Conditional dominance							
Crystallized	Fluid	1	.836	.328	.777	.105	.118
Crystallized	Numeracy	1	.559	.484	.534	.415	.051
Fluid	Numeracy	0	.180	.309	.075	.715	.210
General dominance							
Crystallized	Fluid	1	.879	.326	.879	.121	.000
Crystallized	Numeracy	1	.555	.497	.555	.445	.000
Fluid	Numeracy	0	.112	.316	.112	.888	.000

Note. Analyses were conducted using correlations corrected for measurement error. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table 17. *Dominance Analysis of Under/Overconfidence Regressed on the Predictors*

			Additional contribution of:					
	R^2		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.13**	**(.07, .19)**	**.02**	**(.00, .06)**	**.04**	**(.01, .09)**
Crystal	.13	(.07, .19)			.00	(.00, .01)	.00	(.00, .02)
Fluid	.02	(.00, .06)	.11	(.06, .17)			.02	(.00, .06)
Numeracy	.04	(.01, .09)	.08	(.04, .15)	.00	(.00, .01)		
***k* = 1 average**			**.09**	**(.05, .16)**	**.00**	**(.00, .01)**	**.01**	**(.00, .03)**
Crystallized & Fluid	.13	(.07, .20)					.00	(.00, .01)
Crystallized & Numeracy	.13	(.07, .20)			.00	(.00, .01)		
Fluid & Numeracy	.05	(.02, .09)	.08	(.04, .14)				
***k* = 2 average**			**.08**	**(.04, .14)**	**.00**	**(.00, .01)**	**.00**	**(.00, .01)**
Crystallized & Fluid & Numeracy	.13	(.07, .20)						
Overall average			**.10**	**(.06, .16)**	**.01**	**(.00, .02)**	**.02**	**(.01, .04)**
% of R^2 explained			78%	(44-100%)	7%	(2-19%)	15%	(7-32%)

Note. Analyses were conducted using correlations corrected for measurement error. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table 18. *Bootstrap Results of Dominance Analysis for Under/Overconfidence*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	1	1.000	.000	1.000	.000	.000
Crystallized	Numeracy	1	1.000	.000	1.000	.000	.000
Fluid	Numeracy	0	0.265	.261	0.012	.482	.506
Conditional dominance							
Crystallized	Fluid	1	1.000	.000	1.000	.000	.000
Crystallized	Numeracy	1	1.000	.000	1.000	.000	.000
Fluid	Numeracy	0	0.265	.261	0.012	.482	.506
General dominance							
Crystallized	Fluid	1	1.000	.000	1.000	.000	.000
Crystallized	Numeracy	1	1.000	.000	1.000	.000	.000
Fluid	Numeracy	0	0.039	.194	0.039	.961	.000

Note. Analyses were conducted using correlations corrected for measurement error. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table 19. *Dominance Analysis of Applying Decision Rules Regressed on the Predictors*

			Additional contribution of:					
	R^2_{YX}		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.43**	**(.35, .50)**	**.42**	**(.33, .50)**	**.49**	**(.42, .56)**
Crystal	.43	(.35, .50)			.13	(.09, .19)	.12	(.08, .17)
Fluid	.42	(.33, .50)	.15	(.10, .21)			.15	(.11, .21)
Numeracy	.49	(.42, .56)	.06	(.03, .09)	.08	(.04, .13)		
***k* = 1 average**			**.10**	**(.07, .15)**	**.11**	**(.07, .15)**	**.14**	**(.10, .18)**
Crystallized & Fluid	.57	(.49, .64)					.05	(.02, .08)
Crystallized & Numeracy	.55	(.48, .61)			.06	(.03, .1)		
Fluid & Numeracy	.57	(.50, .64)	.04	(.02, .07)				
***k* = 2 average**			**.04**	**(.02, .07)**	**.06**	**(.03, .1)**	**.05**	**(.02, .08)**
Crystallized & Fluid & Numeracy	.61	(.55, .68)						
Overall average			**.19**	**(.15, .23)**	**.20**	**(.15, .24)**	**.22**	**(.19, .26)**
% of R^2 explained			31%	(25-38%)	33%	(24-40%)	36%	(7-32%)

Note. Analyses were conducted using correlations corrected for measurement error. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table 20. *Bootstrap Results of Dominance Analysis for Applying Decision Rules*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	.5	.423	.375	.216	.370	.414
Crystallized	Numeracy	0	.234	.290	.043	.574	.383
Fluid	Numeracy	.5	.389	.250	.039	.261	.700
Conditional dominance							
Crystallized	Fluid	.5	.423	.375	.216	.370	.414
Crystallized	Numeracy	0	.234	.290	.043	.574	.383
Fluid	Numeracy	.5	.389	.250	.039	.261	.700
General dominance							
Crystallized	Fluid	0	.476	.500	.476	.524	.000
Crystallized	Numeracy	0	.133	.340	.133	.867	.000
Fluid	Numeracy	0	.187	.390	.187	.813	.000

Note. Analyses were conducted using correlations corrected for measurement error. $D_{ij} = 1 – D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., D_{ij} = 1); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., D_{ij} = 0); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., D_{ij} = .5).

Table 21. *Dominance Analysis of Consistency in Risk Perception Regressed on the Predictors*

			Additional contribution of:					
	R^2_{YX}		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.07**	**(.03, .12)**	**.01**	**(.00, .05)**	**.05**	**(.01, .1)**
Crystal	.07	(.03, .12)			.00	(.00, .01)	.00	(.00, .03)
Fluid	.01	(.00, .05)	.05	(.02, .11)			.03	(.01, .08)
Numeracy	.05	(.01, .1)	.02	(.00, .07)	.00	(.00, .01)		
***k* = 1 average**			**.04**	**(.01, .08)**	**.00**	**(.00, .01)**	**.02**	**(.00, .05)**
Crystallized & Fluid	.07	(.03, .13)					.00	(.00, .03)
Crystallized & Numeracy	.07	(.03, .13)			.00	(.00, .02)		
Fluid & Numeracy	.05	(.02, .10)	.02	(.00, .07)				
***k* = 2 average**			**.02**	**(.00, .07)**	**.00**	**(.00, .02)**	**.00**	**(.00, .03)**
Crystallized & Fluid & Numeracy	.07	(.03, .14)						
Overall average			**.04**	**(.01, .09)**	**.01**	**(.00, .02)**	**.02**	**(.01, .06)**
% of R^2 explained			57%	(20-100%)	14%	(3-26%)	29%	(9-77%)

Note. Analyses were conducted using correlations corrected for measurement error. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table 22. *Bootstrap Results of Dominance Analysis for Consistency in Risk Perception*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	1	.980	.101	.961	.001	.038
Crystallized	Numeracy	1	.818	.378	.804	.169	.027
Fluid	Numeracy	0	.166	.242	.006	.674	.320
Conditional dominance							
Crystallized	Fluid	1	.980	.101	.961	.001	.038
Crystallized	Numeracy	1	.818	.378	.804	.169	.027
Fluid	Numeracy	0	.166	.242	.006	.674	.320
General dominance							
Crystallized	Fluid	1	.996	.063	.996	.004	.000
Crystallized	Numeracy	1	.820	.384	.820	.180	.000
Fluid	Numeracy	0	.024	.153	.024	.976	.000

Note. Analyses were conducted using correlations corrected for measurement error. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table 23. *Dominance Analysis of Resistance to Sunk Cost Regressed on the Predictors*

			Additional contribution of:					
	R^2_{YX}		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.05**	**(.01, .10)**	**.02**	**(.00, .05)**	**.06**	**(.02, .12)**
Crystal	.05	(.01, .10)			.00	(.00, .01)	.02	(.00, .06)
Fluid	.02	(.00, .05)	.03	(.01, .08)			.04	(.01, .09)
Numeracy	.06	(.02, .12)	.01	(.00, .03)	.00	(.00, .01)		
***k* = 1 average**			**.02**	**(.00, .05)**	**.00**	**(.00, .01)**	**.03**	**(.01, .07)**
Crystallized & Fluid	.05	(.02, .10)					.02	(.00, .05)
Crystallized & Numeracy	.07	(.03, .12)			.00	(.00, .01)		
Fluid & Numeracy	.06	(.02, .12)	.01	(.00, .04)				
***k* = 2 average**			**.01**	**(.00, .04)**	**.00**	**(.00, .01)**	**.02**	**(.00, .05)**
Crystallized & Fluid & Numeracy	.07	(.03, .13)						
Overall average			**.02**	**(.01, .06)**	**.01**	**(.00, .02)**	**.04**	**(.01, .08)**
% of R^2 explained			29%	(11-92%)	14%	(5-33%)	57%	(17-100%)

Note. Analyses were conducted using correlations corrected for measurement error. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table 24. *Bootstrap Results of Dominance Analysis for Resistance to Sunk Cost*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	1	.844	.257	.711	.024	.265
Crystallized	Numeracy	0	.294	.446	.277	.690	.033
Fluid	Numeracy	0	.037	.140	.005	.931	.064
Conditional dominance							
Crystallized	Fluid	1	.844	.257	.711	.024	.265
Crystallized	Numeracy	0	.294	.446	.277	.690	.033
Fluid	Numeracy	0	.037	.140	.005	.931	.064
General dominance							
Crystallized	Fluid	1	.962	.191	.962	.038	.000
Crystallized	Numeracy	0	.293	.455	.293	.707	.000
Fluid	Numeracy	0	.010	.100	.010	.990	.000

Note. Analyses were conducted using correlations corrected for measurement error. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table 25. *Summary of Dominance Analysis Results*

	DMC	RF	SN	OC	DR	RP	SC
Complete dominance							
Crystallized ability	F		F, N	F, N		F, N	F
Fluid ability		C					
Numeracy	F	C, F	F	F	C	F	C, F
Conditional dominance							
Crystallized ability	F		F, N	F, N		F, N	F
Fluid ability		C					
Numeracy	F	C, F	F	F	C	F	C, F
General dominance							
Crystallized ability	F		F, N	F, N		F, N	F
Fluid ability		C			C		
Numeracy	C, F	C, F	F	F	C, F	F	C, F

Note. Analyses were conducted using correlations corrected for measurement error. C = crystallized ability, F = fluid ability, N = numeracy, DMC = Decision Making Competence, RF = Resistance to Framing, SN = Recognizing Social Norms, OC = Under/Overconfidence, DR = Applying Decision Rules, RP = Consistency in Risk Perception, SC = Resistance to Sunk Cost.

Table 26. *Hierarchical Regression Models of Overall Decision-Making Competence*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.39		350	-.15***	(-.23, -.06)
		Gender				.02	(-.06, .11)
		Crystallized ability				.44***	(.35, .54)
		Fluid ability				.22***	(.13, .31)
	2	University	.43	.04***	351	-.15***	(-.23, -.06)
		Gender				-.08	(-.17, .01)
		Crystallized ability				.28***	(.17, .39)
		Fluid ability				.11*	(.01, .21)
		Numeracy				.33***	(.20, .47)
2	1	University	.38		349	-.16***	(-.25, -.08)
		Gender				-.16***	(-.25, -.06)
		Numeracy				.62***	(.53, .71)
	2	University	.43	.05***	351	-.15***	(-.23, -.06)
		Gender				-.08	(-.17, .01)
		Numeracy				.33***	(.20, .47)
		Crystallized ability				.28***	(.17, .39)
		Fluid ability				.11*	(.01, .21)

Note. Analyses were conducted using correlations corrected for measurement error. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 27. *Hierarchical Regression Models of Resistance to Framing*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.18		350	-.03	(-.13, .07)
		Gender				.12*	(.02, .22)
		Crystallized ability				.06	(-.05, .17)
		Fluid ability				.36***	(.25, .47)
	2	University	.25	.07***	351	-.03	(-.12, .07)
		Gender				-.02	(-.12, .09)
		Crystallized ability				-.15*	(-.28, -.02)
		Fluid ability				.21***	(.10, .33)
		Numeracy				.44***	(.29, .59)
2	1	University	.21		349	-.02	(-.12, .07)
		Gender				-.02	(-.13, .08)
		Numeracy				.47***	(.36, .57)
	2	University	.25	.04***	351	-.03	(-.12, .07)
		Gender				-.02	(-.12, .09)
		Numeracy				.44***	(.29, .59)
		Crystallized ability				-.15*	(-.28, -.02)
		Fluid ability				.21***	(.10, .33)

Note. Analyses were conducted using correlations corrected for measurement error. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 28. *Hierarchical Regression Models of Recognizing Social Norms*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.04		350	-.04	(-.15, .06)
		Gender				-.02	(-.13, .09)
		Crystallized ability				.17**	(.05, .29)
		Fluid ability				.04	(-.08, .16)
	2	University	.05	.01	351	-.04	(-.15, .06)
		Gender				-.06	(-.18, .06)
		Crystallized ability				.11	(-.04, .25)
		Fluid ability				.00	(-.14, .13)
		Numeracy				.13	(-.04, .31)
2	1	University	.04		349	-.05	(-.15, .06)
		Gender				-.08	(-.20, .03)
		Numeracy				.21***	(.10, .32)
	2	University	.05	.01	351	-.04	(-.15, .06)
		Gender				-.06	(-.18, .06)
		Numeracy				.13	(-.04, .31)
		Crystallized ability				.11	(-.04, .25)
		Fluid ability				.00	(-.14, .13)

Note. Analyses were conducted using correlations corrected for measurement error. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 29. *Hierarchical Regression Models of Under/Overconfidence*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.15		350	-.13*	(-.23, -.03)
		Gender				.05	(-.05, .15)
		Crystallized ability				.36***	(.24, .47)
		Fluid ability				-.05	(-.16, .06)
	2	University	.16	.01	351	-.13*	(-.23, -.03)
		Gender				.09	(-.02, .20)
		Crystallized ability				.42***	(.28, .56)
		Fluid ability				-.01	(-.13, .12)
		Numeracy				-.13	(-.29, .03)
2	1	University	.07		349	-.15**	(-.26, -.05)
		Gender				.01	(-.10, .12)
		Numeracy				.18**	(.07, .29)
	2	University	.16	.09***	351	-.13*	(-.23, -.03)
		Gender				.09	(-.02, .20)
		Numeracy				-.13	(-.29, .03)
		Crystallized ability				.42***	(.28, .56)
		Fluid ability				-.01	(-.13, .12)

Note. Analyses were conducted using correlations corrected for measurement error. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 30. *Hierarchical Regression Models of Applying Decision Rules*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.57		350	-.02	(-.09, .06)
		Gender				.06	(-.02, .13)
		Crystallized ability				.44***	(.36, .52)
		Fluid ability				.42***	(.34, .50)
	2	University	.61	.04***	351	-.02	(-.08, .05)
		Gender				-.05	(-.13, .02)
		Crystallized ability				.27***	(.17, .36)
		Fluid ability				.31***	(.22, .39)
		Numeracy				.36***	(.24, .47)
2	1	University	.51		349	-.03	(-.11, .04)
		Gender				-.16***	(-.24, -.08)
		Numeracy				.76***	(.68, .84)
	2	University	.61	.10***	351	-.02	(-.08, .05)
		Gender				-.05	(-.13, .02)
		Numeracy				.36***	(.24, .47)
		Crystallized ability				.27***	(.17, .36)
		Fluid ability				.31***	(.22, .39)

Note. Analyses were conducted using correlations corrected for measurement error. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 31. *Hierarchical Regression Models of Consistency in Risk Perception*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.12		350	-.23***	(-.33, -.13)
		Gender				-.08	(-.18, .02)
		Crystallized ability				.25***	(.14, .36)
		Fluid ability				-.02	(-.13, .10)
	2	University	.13	.01	351	-.23***	(-.33, -.13)
		Gender				-.13*	(-.24, -.01)
		Crystallized ability				.18*	(.04, .32)
		Fluid ability				-.07	(-.19, .06)
		Numeracy				.15	(-.01, .32)
2	1	University	.11		349	-.24***	(-.34, -.13)
		Gender				-.15**	(-.26, -.04)
		Numeracy				.24***	(.13, .35)
	2	University	.13	.02*	351	-.23***	(-.33, -.13)
		Gender				-.13*	(-.24, -.01)
		Numeracy				.15	(-.01, .32)
		Crystallized ability				.18*	(.04, .32)
		Fluid ability				-.07	(-.19, .06)

Note. Analyses were conducted using correlations corrected for measurement error. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table 32. *Hierarchical Regression Models of Resistance to Sunk Cost*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.05		350	-.03	(-.13, .08)
		Gender				-.05	(-.16, .06)
		Crystallized ability				.21***	(.09, .33)
		Fluid ability				.03	(-.09, .14)
	2	University	.08	.03***	351	-.03	(-.13, .08)
		Gender				-.14*	(-.25, -.02)
		Crystallized ability				.07	(-.07, .22)
		Fluid ability				-.07	(-.19, .06)
		Numeracy				.28**	(.11, .45)
2	1	University	.08		349	-.03	(-.13, .07)
		Gender				-.14*	(-.25, -.03)
		Numeracy				.29***	(.18, .40)
	2	University	.08	.00	351	-.03	(-.13, .08)
		Gender				-.14*	(-.25, -.02)
		Numeracy				.28**	(.11, .45)
		Crystallized ability				.07	(-.07, .22)
		Fluid ability				-.07	(-.19, .06)

Note. Analyses were conducted using correlations corrected for measurement error. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Appendix A: Dominance Analysis with Observed Correlations

Table A1. *Dominance Analysis of Decision-Making Competence Regressed on the Predictors*

			Additional contribution of:					
	R^2		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.19**	**(.11, .27)**	**.12**	**(.06, .19)**	**.17**	**(.10, .23)**
Crystal	.19	(.11, .27)			.04	(.01, .09)	.05	(.02, .10)
Fluid	.12	(.06, .19)	.11	(.05, .18)			.08	(.04, .14)
Numeracy	.17	(.10, .23)	.08	(.03, .13)	.04	(.01, .09)		
***k* = 1 average**			**.09**	**(.04, .15)**	**.04**	**(.01, .09)**	**.07**	**(.03, .12)**
Crystallized & Fluid	.23	(.15, .32)					.03	(.01, .07)
Crystallized & Numeracy	.24	(.16, .33)			.02	(.00, .06)		
Fluid & Numeracy	.21	(.14, .28)	.06	(.02, .11)				
***k* = 2 average**			**.06**	**(.02, .11)**	**.02**	**(.00, .06)**	**.03**	**(.01, .07)**
Crystallized & Fluid & Numeracy	.27	(.18, .36)						
Overall average			**.11**	**(.06, .17)**	**.06**	**(.03, .11)**	**.09**	**(.05, .14)**
% of R^2 explained			41%	(22-66%)	22%	(11-41%)	33%	(18-53%)

Note. Analyses were conducted using observed correlations. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table A2. *Bootstrap Results of Dominance Analysis for Decision Making Competence*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	1	.916	.260	.897	.065	.038
Crystallized	Numeracy	1	.753	.409	.715	.209	.076
Fluid	Numeracy	0	.220	.357	.131	.692	.177
Conditional dominance							
Crystallized	Fluid	1	.916	.260	.897	.065	.038
Crystallized	Numeracy	1	.753	.409	.715	.209	.076
Fluid	Numeracy	0	.220	.357	.131	.692	.177
General dominance							
Crystallized	Fluid	1	.924	.265	.924	.076	.000
Crystallized	Numeracy	1	.749	.434	.749	.251	.000
Fluid	Numeracy	0	.191	.393	.191	.809	.000

Note. Analyses were conducted using observed correlations. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table A3. *Dominance Analysis of Resistance to Framing Regressed on the Predictors*

			Additional contribution of:					
	R^2		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.02**	**(.00, .06)**	**.06**	**(.03, .12)**	**.07**	**(.03, .12)**
Crystal	.02	(.00, .06)			.04	(.01, .09)	.05	(.01, .09)
Fluid	.06	(.03, .12)	.00	(.00, .03)			.03	(.01, .07)
Numeracy	.07	(.03, .12)	.00	(.00, .02)	.03	(.00, .07)		
***k* = 1 average**			**.00**	**(.00, .02)**	**.03**	**(.01, .08)**	**.04**	**(.01, .08)**
Crystallized & Fluid	.07	(.03, .13)					.03	(.00, .06)
Crystallized & Numeracy	.07	(.03, .12)			.02	(.00, .06)		
Fluid & Numeracy	.09	(.05, .16)	.00	(.00, .01)				
***k* = 2 average**			**.00**	**(.00, .01)**	**.02**	**(.00, .06)**	**.03**	**(.00, .06)**
Crystallized & Fluid & Numeracy	.09	(.05, .16)						
Overall average			**.01**	**(.00, .03)**	**.04**	**(.01, .09)**	**.04**	**(.02, .09)**
% of R^2 explained			11%	(3-34%)	44%	(15-93%)	44%	(17-91%)

Note. Analyses were conducted using observed correlations. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table A4. *Bootstrap Results of Dominance Analysis for Resistance to Framing*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	0	.042	.183	.029	.946	.025
Crystallized	Numeracy	0	.036	.178	.030	.958	.012
Fluid	Numeracy	0	.450	.486	.427	.528	.045
Conditional dominance							
Crystallized	Fluid	0	.042	.183	.029	.946	.025
Crystallized	Numeracy	0	.036	.178	.030	.958	.012
Fluid	Numeracy	0	.450	.486	.427	.528	.045
General dominance							
Crystallized	Fluid	0	.035	.184	.035	.965	.000
Crystallized	Numeracy	0	.034	.181	.034	.966	.000
Fluid	Numeracy	0	.450	.498	.450	.550	.000

Note. Analyses were conducted using observed correlations. $D_{ij} = 1 – D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table A5. *Dominance Analysis of Recognizing Social Norms Regressed on the Predictors*

	R^2		Additional contribution of: Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.02**	**(.00, .07)**	**.01**	**(.00, .04)**	**.02**	**(.00, .05)**
Crystal	.02	(.00, .07)			.00	(.00, .03)	.00	(.00, .03)
Fluid	.01	(.00, .04)	.01	(.00, .06)			.01	(.00, .04)
Numeracy	.02	(.00, .05)	.01	(.00, .04)	.00	(.00, .03)		
***k* = 1 average**			**.01**	**(.00, .05)**	**.00**	**(.00, .03)**	**.01**	**(.00, .03)**
Crystallized & Fluid	.02	(.00, .07)					.00	(.00, .03)
Crystallized & Numeracy	.02	(.00, .07)			.00	(.00, .02)		
Fluid & Numeracy	.02	(.00, .06)	.01	(.00, .04)				
***k* = 2 average**			**.01**	**(.00, .04)**	**.00**	**(.00, .02)**	**.00**	**(.00, .03)**
Crystallized & Fluid & Numeracy	.03	(.00, .08)						
Overall average			**.01**	**(.00, .05)**	**.00**	**(.00, .03)**	**.01**	**(.00, .04)**
% of R^2 explained			50%	(4-100%)	< 1%	(0-100%)	50%	(4-100%)

Note. Analyses were conducted using observed correlations. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table A6. *Bootstrap Results of Dominance Analysis for Recognizing Social Norms*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	1	.750	.409	.710	.209	.081
Crystallized	Numeracy	1	.626	.474	.606	.354	.040
Fluid	Numeracy	0	.340	.440	.278	.598	.124
Conditional dominance							
Crystallized	Fluid	1	.750	.409	.710	.209	.081
Crystallized	Numeracy	1	.626	.474	.606	.354	.040
Fluid	Numeracy	0	.340	.440	.278	.598	.124
General dominance							
Crystallized	Fluid	1	.760	.427	.760	.240	.000
Crystallized	Numeracy	1	.618	.486	.618	.382	.000
Fluid	Numeracy	0	.314	.464	.314	.686	.000

Note. Analyses were conducted using observed correlations. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table A7. *Dominance Analysis of Under/Overconfidence Regressed on the Predictors*

			Additional contribution of:					
	R^2		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.07**	**(.02, .15)**	**.01**	**(.00, .05)**	**.02**	**(.00, .06)**
Crystal	.07	(.02, .15)			.00	(.00, .01)	.00	(.00, .02)
Fluid	.01	(.00, .05)	.06	(.02, .12)			.01	(.00, .04)
Numeracy	.02	(.00, .06)	.05	(.01, .11)	.00	(.00, .03)		
***k* = 1 average**			**.05**	**(.01, .12)**	**.00**	**(.00, .02)**	**.01**	**(.00, .03)**
Crystallized & Fluid	.07	(.02, .15)					.00	(.00, .01)
Crystallized & Numeracy	.07	(.02, .15)			.00	(.00, .01)		
Fluid & Numeracy	.02	(.00, .07)	.05	(.01, .10)				
***k* = 2 average**			**.05**	**(.01, .10)**	**.00**	**(.00, .01)**	**.00**	**(.00, .01)**
Crystallized & Fluid & Numeracy	.07	(.03, .15)						
Overall average			**.06**	**(.02, .12)**	**.00**	**(.00, .03)**	**.01**	**(.00, .03)**
% of R^2 explained			86%	(23-100%)	0%	(1-39%)	14%	(3-45%)

Note. Analyses were conducted using observed correlations. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table A8. *Bootstrap Results of Dominance Analysis for Under/Overconfidence*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	1	.994	.074	.993	.005	.002
Crystallized	Numeracy	1	.982	.134	.981	.018	.001
Fluid	Numeracy	0	.379	.373	.186	.428	.386
Conditional dominance							
Crystallized	Fluid	1	.994	.074	.993	.005	.002
Crystallized	Numeracy	1	.982	.134	.981	.018	.001
Fluid	Numeracy	0	.379	.373	.186	.428	.386
General dominance							
Crystallized	Fluid	1	.995	.071	.995	.005	.000
Crystallized	Numeracy	1	.982	.133	.982	.018	.000
Fluid	Numeracy	0	.272	.445	.272	.728	.000

Note. Analyses were conducted using observed correlations. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table A9. *Dominance Analysis of Applying Decision Rules Regressed on the Predictors*

			Additional contribution of:					
	R^2		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.22**	**(.15, .30)**	**.22**	**(.14, .31)**	**.21**	**(.14, .29)**
Crystal	.22	(.15, .30)			.10	(.05, .17)	.08	(.03, .14)
Fluid	.22	(.14, .31)	.10	(.05, .16)			.09	(.04, .14)
Numeracy	.21	(.14, .29)	.09	(.04, .14)	.10	(.05, .16)		
***k* = 1 average**			**.09**	**(.05, .15)**	**.10**	**(.05, .16)**	**.08**	**(.04, 013)**
Crystallized & Fluid	.32	(.25, .40)					.04	(.01, .08)
Crystallized & Numeracy	.30	(.22, .38)			.06	(.03, .11)		
Fluid & Numeracy	.31	(.23, .40)	.05	(.02, .10)				
***k* = 2 average**			**.05**	**(.02, .10)**	**.06**	**(.03, .11)**	**.04**	**(.01, .08)**
Crystallized & Fluid & Numeracy	.36	(.29, .44)						
Overall average			**.12**	**(.07, .18)**	**.13**	**(.07, .19)**	**.11**	**(.07, .16)**
% of R^2 explained			33%	(20-51%)	36%	(21-53%)	31%	(18-46%)

Note. Analyses were conducted using observed correlations. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table A10. *Bootstrap Results of Dominance Analysis for Applying Decision Rules*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	0	.421	.457	.350	.508	.142
Crystallized	Numeracy	1	.627	.452	.567	.313	.120
Fluid	Numeracy	1	.692	.407	.595	.212	.193
Conditional dominance							
Crystallized	Fluid	0	.421	.457	.350	.508	.142
Crystallized	Numeracy	1	.627	.452	.567	.313	.120
Fluid	Numeracy	1	.692	.407	.595	.212	.193
General dominance							
Crystallized	Fluid	0	.423	.494	.423	.577	.000
Crystallized	Numeracy	1	.614	.487	.614	.386	.000
Fluid	Numeracy	1	.679	.467	.679	.321	.000

Note. Analyses were conducted using observed correlations. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table A11. *Dominance Analysis of Consistency in Risk Perception Regressed on the Predictors*

			Additional contribution of:					
	R^2		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.04**	**(.01, .09)**	**.01**	**(.00, .04)**	**.02**	**(.00, .06)**
Crystal	.04	(.01, .09)			.00	(.00, .02)	.00	(.00, .03)
Fluid	.01	(.00, .04)	.03	(.00, .07)			.02	(.00, .05)
Numeracy	.02	(.00, .06)	.02	(.00, .06)	.00	(.00, .02)		
***k* = 1 average**			**.03**	**(.00, .06)**	**.00**	**(.00, .02)**	**.01**	**(.00, .04)**
Crystallized & Fluid	.04	(.01, .09)					.00	(.00, .03)
Crystallized & Numeracy	.04	(.01, .10)			.00	(.00, .01)		
Fluid & Numeracy	.02	(.00, .07)	.02	(.00, .05)				
***k* = 2 average**			**.02**	**(.00, .05)**	**.00**	**(.00, .01)**	**.00**	**(.00, .03)**
Crystallized & Fluid & Numeracy	.04	(.01, .10)						
Overall average			**.03**	**(.00, .07)**	**.00**	**(.00, .02)**	**.01**	**(.00, .04)**
% of R^2 explained			75%	(12-100%)	0%	(2-51%)	25%	(2-93%)

Note. Analyses were conducted using observed correlations. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table A12. *Bootstrap Results of Dominance Analysis for Consistency in Risk Perception*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	1	.958	.190	.948	.033	.019
Crystallized	Numeracy	1	.827	.374	.820	.166	.014
Fluid	Numeracy	0	.221	.347	.117	.675	.208
Conditional dominance							
Crystallized	Fluid	1	.958	.190	.948	.033	.019
Crystallized	Numeracy	1	.827	.374	.820	.166	.014
Fluid	Numeracy	0	.221	.347	.117	.675	.208
General dominance							
Crystallized	Fluid	1	.963	.189	.963	.037	.000
Crystallized	Numeracy	1	.822	.383	.822	.178	.000
Fluid	Numeracy	0	.169	.375	.169	.831	.000

Note. Analyses were conducted using observed correlations. $D_{ij} = 1 – D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$).

Table A11. *Dominance Analysis of Resistance to Sunk Cost Regressed on the Predictors*

			Additional contribution of:					
	R^2		Crystallized		Fluid		Numeracy	
Submodel	Est.	95% CI	Est.	95% CI	Est.	95% CI	Est.	95% CI
Null & *k* = 0			**.01**	**(.00, .05)**	**.00**	**(.00, .03)**	**.01**	**(.00, .05)**
Crystal	.01	(.00, .05)			.00	(.00, .02)	.01	(.00, .03)
Fluid	.00	(.00, .03)	.01	(.00, .04)			.01	(.00, .04)
Numeracy	.01	(.00, .05)	.01	(.00, .03)	.00	(.00, .02)		
***k* = 1 average**			**.01**	**(.00, .03)**	**.00**	**(.00, .02)**	**.01**	**(.00, .03)**
Crystallized & Fluid	.01	(.00, .06)					.00	(.00, .03)
Crystallized & Numeracy	.02	(.00, .06)			.00	(.00, .01)		
Fluid & Numeracy	.01	(.00, .05)	.00	(.00, .03)				
***k* = 2 average**			**.00**	**(.00, .03)**	**.00**	**(.00, .01)**	**.00**	**(.00, .03)**
Crystallized & Fluid & Numeracy	.02	(.00, .06)						
Overall average			**.01**	**(.00, .04)**	**.00**	**(.00, .02)**	**.01**	**(.00, .04)**
% of R^2 explained			50%	(5-100%)	0%	(0-100%)	50%	(5-100%)

Note. Analyses were conducted using observed correlations. R^2 is the criterion variance accounted for by the submodel that includes variables listed in each corresponding row.

Table A12. *Bootstrap Results of Dominance Analysis for Resistance to Sunk Cost*

X_i	X_j	D_{ij}	Mean	*SE*	P_{ij}	P_{ji}	P_{ijno}
Complete dominance							
Crystallized	Fluid	1	.735	.400	.665	.195	.140
Crystallized	Numeracy	0.5	.500	.494	.489	.488	.023
Fluid	Numeracy	0	.248	.388	.176	.680	.144
Conditional dominance							
Crystallized	Fluid	1	.735	.400	.665	.195	.140
Crystallized	Numeracy	0.5	.500	.494	.489	.488	.023
Fluid	Numeracy	0	.248	.388	.176	.680	.144
General dominance							
Crystallized	Fluid	1	.758	.429	.758	.242	.000
Crystallized	Numeracy	0	.500	.500	.500	.500	.000
Fluid	Numeracy	0	.220	.414	.220	.780	.000

Note. Analyses were conducted using observed correlations. $D_{ij} = 1 - D_{ji}$; Mean = average value of D_{ij} over 1,000 bootstrap samples; *SE* = standard error of the D_{ij} values over the samples; P_{ij} = proportion of samples in which X_i dominated X_j (i.e., $D_{ij} = 1$); P_{ji} = proportion of bootstrap samples in which X_j dominated X_i (i.e., $D_{ij} = 0$); P_{ijno} = proportion of samples in which dominance between X_i and X_j could not be determined (i.e., $D_{ij} = .5$)

Appendix B: Hierarchical Regression with Observed Correlations

Table B1. *Hierarchical Regression Models of Overall Decision-Making Competence*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.25		350	-.14**	(-.23, -.05)
		Gender				.03	(-.06, .12)
		Crystallized ability				.34***	(.24, .43)
		Fluid ability				.21***	(.12, .31)
	2	University	.28	.03***	351	-.14**	(-.23, -.04)
		Gender				-.02	(-.12, .07)
		Crystallized ability				.27***	(.16, .37)
		Fluid ability				.16**	(.06, .26)
		Numeracy				.21***	(.10, .32)
2	1	University	.19		349	-.16**	(-.26, -.06)
		Gender				-.05	(-.15, .05)
		Numeracy				.40***	(.30, .50)
	2	University	.28	.09***	351	-.14**	(-.23, -.04)
		Gender				-.02	(-.12, .07)
		Numeracy				.21***	(.10, .32)
		Crystallized ability				.27***	(.16, .37)
		Fluid ability				.16**	(.06, .26)

Note. Analyses were conducted using observed correlations. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table B2. *Hierarchical Regression Models of Resistance to Framing*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.08		350	-.02	(-.13, .08)
		Gender				.09	(-.01, .20)
		Crystallized ability				.07	(-.04, .17)
		Fluid ability				.22***	(.11, .33)
	2	University	.10	.02**	351	-.02	(-.13, .08)
		Gender				.05	(-.06, .16)
		Crystallized ability				.01	(-.11, .12)
		Fluid ability				.18**	(.06, .29)
		Numeracy				.17**	(.05, .29)
2	1	University	.07		349	-.03	(-.13, .08)
		Gender				.04	(-.07, .15)
		Numeracy				.25***	(.14, .35)
	2	University	.10	.03**	351	-.02	(-.13, .08)
		Gender				.05	(-.06, .16)
		Numeracy				.17**	(.05, .29)
		Crystallized ability				.01	(-.11, .12)
		Fluid ability				.18**	(.06, .29)

Note. Analyses were conducted using observed correlations. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table B3. *Hierarchical Regression Models of Recognizing Social Norms*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.02		350	-.04	(-.15, .07)
		Gender				-.02	(-.12, .09)
		Crystallized ability				.12*	(.01, .23)
		Fluid ability				.05	(-.06, .16)
	2	University	.03	.00	351	-.04	(-.15, .07)
		Gender				-.03	(-.15, .08)
		Crystallized ability				.10	(-.02, .22)
		Fluid ability				.03	(-.09, .14)
		Numeracy				.08	(-.05, .20)
2	1	University	.02		349	-.05	(-.16, .06)
		Gender				-.04	(-.15, .07)
		Numeracy				.13*	(.02, .24)
	2	University	.03	.01	351	-.04	(-.15, .07)
		Gender				-.03	(-.15, .08)
		Numeracy				.08	(-.05, .20)
		Crystallized ability				.10	(-.02, .22)
		Fluid ability				.03	(-.09, .14)

Note. Analyses were conducted using observed correlations. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table B4. *Hierarchical Regression Models of Under/Overconfidence*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.09		350	-.12*	(-.22, -.02)
		Gender				.05	(-.05, .15)
		Crystallized ability				.24***	(.13, .35)
		Fluid ability				.01	(-.10, .12)
	2	University	.09	.00	351	-.12*	(-.22, -.02)
		Gender				.05	(-.06, .16)
		Crystallized ability				.24***	(.13, .36)
		Fluid ability				.01	(-.10, .12)
		Numeracy				.00	(-.12, .12)
2	1	University	.04		349	-.14*	(-.24, -.03)
		Gender				.03	(-.08, .15)
		Numeracy				.12*	(.01, .22)
	2	University	.09	.05***	351	-.12*	(-.22, -.02)
		Gender				.05	(-.06, .16)
		Numeracy				.00	(-.12, .12)
		Crystallized ability				.24***	(.13, .36)
		Fluid ability				.01	(-.10, .12)

Note. Analyses were conducted using observed correlations. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table B5. *Hierarchical Regression Models of Applying Decision Rules*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.33		350	-.02	(-.11, .07)
		Gender				.06	(-.03, .15)
		Crystallized ability				.34***	(.24, .43)
		Fluid ability				.34***	(.25, .43)
	2	University	.36	.03***	351	-.02	(-.11, .07)
		Gender				.00	(-.09, .09)
		Crystallized ability				.26***	(.16, .36)
		Fluid ability				.28***	(.19, .38)
		Numeracy				.22***	(.12, .33)
2	1	University	.21		349	-.05	(-.15, .05)
		Gender				-.03	(-.13, .07)
		Numeracy				.46***	(.37, .56)
	2	University	.36	.15***	351	-.02	(-.11, .07)
		Gender				.00	(-.09, .09)
		Numeracy				.22***	(.12, .33)
		Crystallized ability				.26***	(.16, .36)
		Fluid ability				.28***	(.19, .38)

Note. Analyses were conducted using observed correlations. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table B6. *Hierarchical Regression Models of Consistency in Risk Perception*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.08		350	-.20***	(-.31, -.10)
		Gender				-.06	(-.17, .04)
		Crystallized ability				.17**	(.06, .28)
		Fluid ability				.02	(-.09, .13)
	2	University	.08	.00	351	-.20***	(-.31, -.10)
		Gender				-.09	(-.20, .02)
		Crystallized ability				.14*	(.02, .26)
		Fluid ability				-.01	(-.12, .11)
		Numeracy				.09	(-.03, .21)
2	1	University	.07		349	-.21***	(-.32, -.11)
		Gender				-.10	(-.20, .01)
		Numeracy				.15**	(.05, .26)
	2	University	.08	.01	351	-.20***	(-.31, -.1)
		Gender				-.09	(-.20, .02)
		Numeracy				.09	(-.03, .21)
		Crystallized ability				.14*	(.02, .26)
		Fluid ability				-.01	(-.12, .11)

Note. Analyses were conducted using observed correlations. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.

Table B7. *Hierarchical Regression Models of Resistance to Sunk Cost*

Model	Step	Variable	R^2	ΔR^2	*df*	β	95% CI
1	1	University	.02		350	-.02	(-.13, .09)
		Gender				-.03	(-.14, .08)
		Crystallized ability				.11	(-.01, .22)
		Fluid ability				.03	(-.08, .14)
	2	University	.02	.00	351	-.02	(-.13, .09)
		Gender				-.05	(-.17, .06)
		Crystallized ability				.07	(-.05, .20)
		Fluid ability				.01	(-.11, .12)
		Numeracy				.10	(-.03, .22)
2	1	University	.02		349	-.03	(-.13, .08)
		Gender				-.06	(-.17, .05)
		Numeracy				.13	(.02, .24)
	2	University	.02	.00	351	-.02	(-.13, .09)
		Gender				-.05	(-.17, .06)
		Numeracy				.10	(-.03, .22)
		Crystallized ability				.07	(-.05, .20)
		Fluid ability				.01	(-.11, .12)

Note. Analyses were conducted using observed correlations. University is coded 0 = MTU, 1 = OU, Gender is coded 0 = Female, 1 = Male, *df* = degrees of freedom; β = standardized beta coefficient.
* $p < .05$; ** $p < .01$; *** $p < .001$.