Decision-making competence and cognitive abilities: Which abilities matter?

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Abstract
Decision-making competence is a skill that is associated with numerous positive life outcomes. Even though multiple cognitive abilities have been shown to predict decision-making competence, few studies have incorporated a large test battery tapping into several cognitive abilities concurrently in the same models. The current paper presents a study that sought to investigate which cognitive abilities predicted overall decision-making competence in adults using hierarchical regression analysis. A cognitive test battery, comprising abilities such as general intelligence, executive functions, numeracy, visuospatial ability, and time perception, was administered to 182 participants. Results indicate that both general intelligence, which was consistently the strongest predictor, and numeracy contributed independently to overall decision-making competence. Executive functions did predict overall decision-making competence, while all predictors were included in the models. A novel finding concerns the relationship between time perception and decision-making competence. The complementary roles of these cognitive abilities are discussed.

Keywords
cognitive abilities, decision-making competence, executive functions, intelligence, numeracy, time perception

1 INTRODUCTION

Decision making is a pervasive feature of everyday life encompassing both trivial activities, such as deciding what to eat for lunch, and more pressing and existential issues with potentially detrimental consequences, such as whether to undergo a risky surgical procedure or to invest in the stock market. Initial models of human decision making have traditionally viewed human decision outcomes as products of rational, cognitive processing where the probability and the utility of each alternative are clearly and exhaustively calculated. However, pioneering research has shown that individuals consistently fall prey to various behavioral biases, such as the framing effect (Tversky & Kahneman, 1981) and sunk costs (Arkes & Blumer, 1985), that runs counter to the notion that humans adhere to traditional normative theories of decision making.

Mounting evidence suggests that there are stable individual differences in how susceptible people are to various decision-making biases and how well people adhere to normative principles (Bruine de Bruin et al., 2007; Parker et al., 2018). A comprehensive multifaceted test has been developed called the “Adult Decision-Making Competence” (A-DMC) test (Bruine de Bruin et al., 2007), which consists of six subcomponents that together capture an overall estimate of “decision-making competence.” The A-DMC has been demonstrated to be related to normative outcomes such as socioeconomic status, less maladaptive and risky behavior in youth, antisocial behavior, substance abuse, and adolescent delinquency (Parker et al., 2018).
Therefore, the value of knowing what individual and social circumstances give rise to greater decision-making skills cannot be overstated. Decision-making competence has been linked to several individual characteristics, such as personality variables (Weller et al., 2018) and decision-making styles (Dewberry et al., 2013), as well as individual cognitive abilities. Performance on the A-DMC is intricately tied to individual cognitive abilities, where studies have shown correlations with general intelligence (Bruine de Bruin et al., 2007), executive functions (EFs; Del Missier et al., 2012), numeracy (Del Missier et al., 2012), and memory capacity (Del Missier et al., 2013). Even though a multitude of cognitive abilities has been shown to predict decision-making competence, few studies have incorporated a large test battery tapping into several cognitive abilities concurrently in the same models. Given that these cognitive abilities, as well as the neural mechanisms subserving them, are overlapping and interlinked, it is essential to investigate models where multiple abilities are taken into account. Otherwise, there is a risk that any study investigating the influence of a single cognitive ability (e.g., general intelligence) may fail to reveal a genuine effect of a third and related factor (e.g., working memory [WM]) that correlates with the ability used in the analysis. In addition, the superior decision making is likely supported by a complex orchestration of several cognitive abilities, thus warranting further investigation of these putative associations. The current paper presents a study that sought to investigate which cognitive abilities predicted overall decision-making competence in adults using hierarchical regression analysis. Below, we provide an overview of previous studies that have looked into the relationship between various cognitive abilities and decision-making competence. First, we will present previous research on DMC and the relation with intelligence and EF, after which we provide an overview of previous research on DMC and spatial and temporal processing. Last, we will highlight research on various numerical abilities and their role in DMC (see Table 1 for an overview of prior research reporting correlations between DMC and cognitive abilities).

### 1.1 Decision-making competence, intelligence, and EFs

General cognitive abilities, such as EFs and intelligence, have consistently been linked to various aspects of decision-making competence. One conventional way of assessing general intelligence is by administering Raven’s Progressive Matrices (RPM; Raven, 1976). General intelligence—or “g”—can be conceptualized as the apex of a hierarchy of several underlying abilities (Carroll, 1993), where “fluid” intelligence and “crystallized” intelligence are primary components that constitute g (Cattell, 1963; Horn, 1968). Fluid intelligence refers to the ability to reason about and solve novel problems that require an understanding of new rules or concepts, while crystallized intelligence denotes the ability to reason using previous experience and learned concepts. Intelligence is prima facie face to be associated with decision-making competence. The ability to acquire knowledge and reason about cognitively complex information, regardless of the domain, should support the development of decision-making skills. Empirically, this conjecture seems to hold true. Work by Bruine de Bruin et al. (2007) showed that scores on RPM were correlated with overall DMC as well as each subcomponent of DMC. This is also corroborated by Del Missier et al. (2012) and Román et al. (2019) who showed that fluid intelligence was linked to several aspects of decision-making competence. In fact, some researchers have argued that decision-making competence as a construct is so intertwined with general intelligence that measures of individual differences in decision-making competence are in fact just tapping into general intelligence (e.g., Blacksmith et al., 2019). However, Bruine de Bruin et al. (2020) emphasize that DMC is correlated with decision outcomes even when controlling for fluid intelligence. Nevertheless, it is clear that intelligence is an important predictor of decision-making competence, whose role should be illuminated by incorporating additional measures of cognitive ability in the models.

Although intelligence is arguably important in various decision-making domains, some researchers have highlighted that other general cognitive abilities are equally important. Del Missier et al. (2012) found that, in addition to intelligence, measures of EFs contributed to decision-making competence. EF is an umbrella term for different cognitive control processes that are involved in the regulation of cognition and behavior (Miyake et al., 2000; Miyake & Friedman, 2012). EFs have been studied extensively within cognitive psychology and cognitive neuroscience, and EF has been linked to a multitude of positive outcomes, such as financial outcomes (Ballinger et al., 2011) and mental and physical health (Moffitt et al., 2011). The predominant model of EF was formulated by Miyake et al. (2000) and consists of three interrelated components— inhibition, shifting, and WM/updating. These three components interact during cognitive processing and are subserved by a central executive network in the brain, comprising nodes in the dorsolateral prefrontal cortex and the posterior parietal cortex (Menon & Uddin, 2010; Sherman et al., 2014). These areas of the brain, and the tasks tapping into EF, are often implicated in various neural conditions, such as attention deficit hyperactivity disorder (ADHD) (Diamond, 2005) and Alzheimer’s disease (Baudic et al., 2006).

With respect to decision-making competence, studies have found that different components of EF predict different aspects of decision-making competence (Del Missier et al., 2010; Del Missier et al., 2012). For example, inhibition was more tied to the aspect “applying decision rules,” whereas shifting was linked to the “consistency in risk perception” aspect (Del Missier et al., 2012). In related work, Rosi et al. (2019) found that WM capacity mediated the age-related decline in “applying decision rules.” Thus, all three aspects of EF contribute to decision-making competence.

### 1.2 Decision-making competence, spatial, and temporal processing

Visuospatial cognitive ability refers to the capacity to perceive and reason about visuospatial properties in the environment, which is
another candidate ability that is likely to contribute to better decision making. This visuospatial ability is called upon in multiple levels of spatial processing; playing chess and imagining prospective moves is at a lower level, whereas navigating in an unfamiliar city constitutes a higher level. These levels are interrelated both cognitively and neurologically in the human brain and are grounded in our overall ability to process space (Hegarty et al., 2006). Research has consistently shown that individual spatial abilities vary substantially in the population. In addition, superior visuospatial ability is strongly linked to various positive outcomes, such as achieving professional success in science, technology, engineering, and mathematics (STEM) fields, such as engineering and mathematics that rely heavily on reasoning about visuospatial elements (Wai et al., 2009) and learning mathematics in childhood (Verdine et al., 2014). Research on the impact of visuospatial abilities on decision making is scarce, but the visuospatial ability has been associated with better decision making in the elderly (Gamble et al., 2015; Han et al., 2015). Thus, visuospatial abilities are likely involved in decision-making competence, but the specific relationship is unclear, especially when taking additional abilities into account.

Good decision making is not only about making the right decision among a set of alternatives but also doing it at the right time. In addition, the time it takes until a beneficial outcome is received can be viewed as a cost and is weighted against the value of the outcome (Wittmann & Paulus, 2008). There are individual differences in how people reason about temporal aspects; some individuals are more patient in their choices of saving versus consumption, whereas other individuals seek to ensure immediate gratification. As such, time

| Research                         | DMC task                      | Intelligence | EF—WM | EF—shifting | EF—inhibition | Numerical ability |
|----------------------------------|-------------------------------|--------------|-------|-------------|---------------|------------------|
| Bruine de Bruin et al. (2007)    | Overall DMC                   |              |       |             |               |                  |
| Bruine de Bruin et al. (2007)    | Social norms                  | r = .61      | -     | -           | -             |                  |
| Bruine de Bruin et al. (2007)    | Framing                       | r = .37      | -     | -           | -             |                  |
| Bruine de Bruin et al. (2007)    | Underconfidence/overconfidence| r = .29      | -     | -           | -             |                  |
| Bruine de Bruin et al. (2007)    | Decision rules                | r = .65      | -     | -           | -             |                  |
| Bruine de Bruin et al. (2007)    | Risk perception               | r = .40      | -     | -           | -             |                  |
| Del Missier et al. (2010)        | Decision rules                |              | r = .26 |              | r = .27       |                  |
| Del Missier et al. (2010)        | Risk perception               |              | n.s.  | r = .33     | n.s.          |                  |
| Del Missier et al. (2012)        | Social norms                  |              | n.s.  | n.s.        | r = .15       | n.s.             |
| Del Missier et al. (2012)        | Framing                       | r = .17      | n.s.  | n.s.        | r = .18       | n.s.             |
| Del Missier et al. (2012)        | Underconfidence/overconfidence| n.s.         | r = .36 | n.s.        | r = .14       | n.s.             |
| Del Missier et al. (2012)        | Decision rules                | r = .43      | r = .31 | n.s.        | r = .14       | r = .42          |
| Del Missier et al. (2012)        | Risk perception               | r = .21      | n.s.  | r = .20     | n.s.          | r = .28          |
| Del Missier et al. (2012)        | Sunk costs                    | r = .17      | n.s.  | n.s.        | n.s.          | r = .20          |
| Del Missier et al. (2013)        | Social norms                  |              | n.s.  | -           | -             |                  |
| Del Missier et al. (2013)        | Framing                       |              | r = .21 | -           | -             |                  |
| Del Missier et al. (2013)        | Underconfidence/overconfidence|              | r = .20 | -           | -             |                  |
| Del Missier et al. (2013)        | Decision rules                |              | r = .34 | -           | -             |                  |
| Del Missier et al. (2013)        | Risk perception               |              | n.s.  | -           | -             |                  |
| Del Missier et al. (2013)        | Sunk costs                    |              | n.s.  | -           | -             |                  |
| Román et al. (2019)              | Social norms                  | r = .13      | -     | -           | -             |                  |
| Román et al. (2019)              | Framing                       | r = .24      | -     | -           | -             |                  |
| Román et al. (2019)              | Underconfidence/overconfidence| n.s.         | -     | -           | -             |                  |
| Román et al. (2019)              | Decision rules                | r = .40      | -     | -           | -             |                  |
| Román et al. (2019)              | Risk perception               | r = .22      | -     | -           | -             |                  |
| Román et al. (2019)              | Sunk costs                    | r = .22      | -     | -           | -             |                  |
| Parker et al. (2018)             | Overall DMC                   |              |       | -           | r = .30       |                  |
| Rosi et al. (2019)               | Decision rules                |              | r = .46 | r = .65     | r = .58       |                  |
| Sinayev and Peters (2015)        | Risk perception               | r = .20      | -     | -           | -             | r = .25          |
| Sinayev and Peters (2015)        | Framing                       | r = .16      | -     | -           | -             | r = .17          |
| Sinayev and Peters (2015)        | Underconfidence/overconfidence| r = .10      | -     | -           | -             | r = .08          |

Abbreviations: EF, executive function; DMC, Decision-Making Competence; WM, working memory; n.s. = non-significant.
management is a pertinent aspect of decision making where the temporal discounting of various choices has to be taken into account (Frederick et al., 2002). Thus, value functions about health and wealth have to factor in when one can expect to reap the benefits of the choices one makes—receiving a dollar today is worth more than receiving a dollar tomorrow. This is an instance of intertemporal choice (Frederick et al., 2002), and studies have shown that there are individual differences in how people estimate the cost of time, where impulsive traits have been linked to a preference toward temporal discounting (Paasche et al., 2019). Related research on consumer behavior has shown that how individuals map objective future time onto a nonlinear subjective perception of time drive intertemporal preferences (Zauberman et al., 2009) and that these preferences can vary depending on whether the consumption concerns material or experiential goods (Goodman et al., 2019). In addition, studies have shown that individuals with higher intelligence (Burks et al., 2009) and higher EF (Basile & Toplak, 2015) were more patient and tended to discount intertemporal choices to a lesser degree. Although studies have established a relationship between temporal discounting and decision making, to our knowledge, no one has investigated whether time perception ability influences decision-making competence.

Time perception has been studied extensively in psychology and cognitive neuroscience, where one pioneering model was named the “Pacemaker-Accumulator-Model” (e.g., Church, 1984; Meck, 1983). According to this model, the processing of temporal information is carried out in three synchronized systems: One system—the clock system—is a dopaminergic system that feeds units, or temporal pulses or neural ticks, through a “gate system” and into an accumulator. The stimulus-dependent information stored in the accumulator is then fed into WM, in prefrontal and parietal cortices, for decision making. Indeed, executive functioning is intrinsically connected with time perception as EFs are involved in planning for the future. Mioni et al. (2017) found a moderate correlation between time perception and WM in children. Some have argued that memory deficits that are manifest in children with ADHD may be caused by an abnormally fast internal counting process that affects time perception ability (Marx et al., 2017). Neurologically, Wittmann and van Wassenhove (2009) have shown that the neurological underpinnings of time perception are very close to those associated with ADHD. Studies have also suggested that everyday multitasking, and by extension successfully managing complex decisions, requires sequential planning and execution of actions that could be supported by spatiotemporal processes (Mäntylä et al., 2017; Todorov et al., 2018). Therefore, we expect that time perception ability is associated with decision-making competence above and beyond the influence of EF, even if they are interrelated constructs.

### 1.3 Decision-making competence and numerical ability

It stands to reason that being numerate is imperative in today’s society in order to make important and informed decisions, such as about one’s financial situation and medical issues. These decisions often involve making decisions involving numbers. For example, these numbers may express probabilities, quantities, and frequencies that must be accurately decoded and put into a specific context for the decision maker. Thus, not only must one be able to read and write adequately, but one must also be proficient in understanding and using numbers. The degree one can do this is called numeracy (Peters et al., 2006; Reyna et al., 2009), and mounting evidence highlights the importance of this skill to decision making. For example, within the domain of health numeracy, findings by Schwartz et al. (1997) demonstrated that greater numeracy was associated with a better understanding of the benefits of mammography. In a similar vein, Peters et al. (2007) found that individuals with lower numeracy struggled more than more numerate individuals in comprehending medical information that was unordered or contained superfluous information. Thus, being more numerate, in terms of understanding percentages and ratios, is linked to understanding the risks and benefits of medical information. Also, numeracy accounts for a unique variance of normative decision making when controlling for effects of education and income (Cavanaugh et al., 2008) and general intelligence (Peters et al., 2006). Numeracy can also serve as a buffer against motivated reasoning when it comes to interpreting political facts (Lind et al., 2018). Work by Woloshin et al. (1999) suggests that individuals with low numeracy may show difficulties using frequencies and percentages in a consistent manner (e.g., transforming information from one format to another) and may encourage these individuals to rely on affective interpretations of information about risks and benefits.

Besides the health domain, research on numeracy and decision making has shown consistent associations between numeracy and decision making involving numbers (e.g., Peters et al., 2006). More numerate individuals are also less susceptible to framing effects and draw more accurate affective meaning from numbers that guide decisions. In terms of the framing effect, it seems that highly numerate individuals can transform numbers from one mode of presentation to another (e.g., percentages to frequencies) more readily and thus have both formats available for comparison. A recent study also found that numeracy was a robust predictor of superior decision making and financial outcomes (Sinayev & Peters, 2015). Thus, extensive research shows consistent links between superior decision making and numeracy that is independent of general intelligence and education. However, it is still unclear how decision-making competence relates to other numerical competencies, such as arithmetic abilities or the innate intuitive sense of nonsymbolic number—the number sense (Dehaene, 2011; Halberda et al., 2008). The number sense refers to the empirical fact that human beings are endowed with an innate domain-specific ability to represent and manipulate quantities (Dehaene, 2011; Gelman & Butterworth, 2005), which is an ability phylogenetically shared with other primates and animals (Dehaene, 2011; Feigenson et al., 2004). It has been suggested that this representational system provides the foundation onto which the culturally acquired symbolic system—mathematics—is mapped (Feigenson et al., 2004). Within the domain of mathematical cognition, the number sense has been extensively studied in terms of how it
relates to mathematical abilities (e.g., Halberda et al., 2008; Libertus et al., 2011) and to developmental dyscalculia (e.g., Mazzocco et al., 2011; Rousselle & Noël, 2007; Skagerlund & Träff, 2014). The ability to discriminate between sets of objects has been linked to better mathematical abilities and also to developmental dyscalculia. Previous studies have found a relationship between normative decision making and affinity with numerical symbols and mapping them to their underlying magnitude (cf. Peters et al., 2008; Peters & Bjälkebring, 2015; Petrova et al., 2014; Schley & Peters, 2014; Sobkow et al., 2020; see also Patalano et al., 2015). We add to the current literature by investigating if acuity of the innate number sense, which is devoid of symbols, is related to DMC. Thus, to get a nuanced view of how overall affinity with numbers influences decision-making competence, we include a set of measures tapping into different aspects of numerical abilities.

1.4 | The present study

Our objective was to gain a better understanding of the cognitive underpinnings supporting decision-making competence in adults using a comprehensive test battery that extends previous efforts and insights. A novel contribution resides in including several unexplored predictors that can yield additional knowledge, beyond previously known predictors, about the cognitive abilities subserving decision-making competence.

We assessed the relative contributions of general cognitive abilities, such as general intelligence, EF, visuospatial ability, and time perception on different aspects of decision making as well as an overall composite score of decision-making competence. Above and beyond those general abilities, we assessed the contribution of different aspects of numeracy; these aspects consisted of written arithmetic, numeracy (i.e., Berlin Numeracy Test [BNT]), and number sense. To investigate these putative associations, we used hierarchical multiple regression modeling to investigate the relative importance of these cognitive abilities. This allows us to insert control variables, such as age and gender, and incrementally include blocks with previously known predictors, such as intelligence and EF. Although the current approach is mainly explorative, we expect that intelligence, EF, and numeracy to be predictive of decision-making competence, while we remain agnostic as to the role of the other cognitive abilities.

2 | METHOD

2.1 | Participants

The participants consisted of university students enrolled at Linköping University in Sweden and were recruited from varying academic disciplines. An a priori power analysis, based on a Cohen’s $f^2 > .15$ (a medium-sized effect; Cohen, 1988), with 11 predictors and an alpha level of .05, and a desired statistical power of 95%, the minimum sample size was calculated to $N = 179$. Two participants did not complete both sessions (one male and one female), so the final sample ($N = 182$) consisted of 93 women and 89 men with a mean age of 24.00 ($SD = 3.35$). All participants had Swedish as their native language and had a normal or corrected-to-normal vision. The participants gave their informed and written consent. The study was approved by the local ethics committee and conformed to the Helsinki convention. After completing the study, the participants were given $100 as compensation for their participation.

2.2 | Assessment of decision-making competence

Decision-making competence was measured using the A-DMC (Bruine de Bruin et al., 2007), which consists of six subcomponents across 192 items. The subcomponents consist of resistance to framing, recognizing social norms, underconfidence/overconfidence, applying decision rules, consistency in risk perception, and resistance to sunk costs (see supporting information for details or see Bruine de Bruin et al., 2007).

2.3 | Assessment of general cognitive abilities

2.3.1 | General intelligence

To assess general intelligence, we administered a short version of Raven’s Advanced Progressive Matrices (RAPM; Raven et al., 1988) developed and normed by Bors and Stokes (1998). This version contains 12 items taken from the original RAPM that have proven to be a useful and valid proxy for the full-length RAPM ($r = .92$ correlation with full RAPM; Bors & Stokes, 1998) with internal consistency of $\alpha = .71$ (Bors & Stokes, 1998). Each test item contained a figure, or matrix, with a set of elements that together complete a logical pattern involving both horizontal and vertical transformations. For each test item, there is one missing piece of the figure. The participant has to deduce which figure, out of eight alternatives, would complete the pattern. The participants had 15 min at their disposal to solve as many problems as possible. The number of correctly answered problems was the dependent measure.

2.3.2 | EFs

Inhibition was measured using a traditional color Stroop task, which we have used previously (e.g., Skagerlund & Träff, 2014; Strömbäck et al., 2020). Each subject was presented with a piece of paper with 30 color words written in two separate columns. This test was divided into two conditions: one with congruent color words and one with incongruent color words. Each condition was completed twice, resulting in 60 words in each of the two conditions. The subject was to identify and read aloud as fast as possible the color with which the words were written. Immediately upon completion of one round of 30 words of a given condition, the subject went on to the next round
when ready. An experimenter used a stopwatch to measure the time in seconds it took to read all 30 words in each round in each condition. The mean response time of the incongruent condition was used as an index of inhibition. A split-half reliability coefficient was calculated to .90.

Shifting ability was assessed using a paper-and-pencil version of the Trail Making Test (van der Sluis et al., 2004), which contained two conditions. The first condition (A) contained 22 circles, each containing a digit, whereas the second condition (B) also contained 22 circles but now with either a digit or a letter written in it. In Condition A, the task was to draw a line and connect the circles in ascending order as fast as possible. In Condition B, the participants are told to draw the line and connect the circles in ascending order once again, but now in alternating order (1-A-2-B-3-C, etc.) and as quickly as possible without making any mistakes. The dependent measure was the number of seconds for each condition it took for the participant to connect all of the circles. The condition requiring shifting between digits and letters was used as an index of shifting ability.

The WM subcomponent of EF was assessed using the digit span subtest of the Wechsler Adult Intelligence Scale-IV (WAIS-IV; Wechsler, 2008). This subtest is divided into three conditions: Digit Span Forward, Digit Span Backward, and Digit Span Sequencing. In the first condition, the participant hears a series of digits and attempts to repeat them out loud in order. In contrast, in the Digit Span Backward condition, the participant has to repeat the string of digits in reverse order. The sequencing condition requires the participant to recall all the digits in the correct ordinal sequence. All conditions become increasingly more difficult in terms of the number of digits there are to be repeated. The maximum score for each condition is 16 for a total of 48 for the entire task. Cronbach’s alpha was calculated by checking the internal consistency across each subtest of WAIS-IV and resulted in \( \alpha = .71 \).

### 2.3.3 | Visuospatial ability

A mental rotation task was used to assess visuospatial ability, developed by Neuberger et al. (2011). This paper-and-pencil test contained 16 items, consisting of block figures in various configurations, based on earlier work by Shepard and Metzler (1971) and Vandenberg and Kuse (1978). Each item consists of a reference figure, where the reference was located on the left side accompanied by four comparison stimuli located on the right side adjacent to the target. The comparison stimuli always consisted of two “correct” and two “incorrect” items. The primary task was to identify the two matching items and respond by marking them with a pencil. The incorrect items were visually mirrored instances of the correct target. All comparison stimuli were rotated in the picture-plane and in one of six rotation angles: 45°, 90°, 135°, 225°, 270°, or 315°. The participants had to mark both correct comparison stimuli to obtain one point for each item, yielding a maximum score for each subtest of 16 and 32 for the entire test. The internal consistency was calculated to \( \alpha = .80 \).

### 2.3.4 | Time perception

The perception of time was measured using a time discrimination task (see Skagerlund & Träff, 2014). The task was to estimate which of two visually presented stimuli was presented the longest. The participant was presented with a reference stimulus (a red ball) centered on the screen, on a white background. The reference stimulus presentation lasted for 3000 ms, followed by a blank screen for 500 ms, after which a target stimulus (a blue ball) appeared centered on the screen. After the target stimulus disappeared, a response screen followed prompting a response. The reference was always presented for 3000 ms and before the target, whereas the target stimuli duration ranged from 1500 to 6000 ms. The participant pressed either the “a” key (marked with red) or the blue-marked “*” key. The test included four practice trials and the participants were asked not to use any counting strategies, such as subvocal counting, during the task. The internal consistency coefficient was calculated to .71.

### 2.4 | Assessment of numerical ability

#### 2.4.1 | Numeracy

Numeracy was measured using the BNT, developed by Cokely et al. (2012) and validated in Swedish by Lindskog et al. (2015). This scale was chosen because it has proven to be normally distributed in an educated population and has shown good discriminant and convergent validity with other cognitive tests (Cokely et al., 2012). The BNT consists of four items (e.g., “Imagine we are throwing a five-sided die 50 times. On average, out of these 50 throws how many times would this five-sided die show an odd number [1, 3 or 5]?”). The BNT can be administered in an adaptive format, which is less time consuming and requires that the participant only completes three problems. However, we chose to use all four items of the scale and sum up all correct answers as an index of numeracy, which is a procedure suggested as a valid alternative by Cokely et al. (2012). The participants had 10 min at their disposal to solve all four items of the BNT. Cronbach’s alpha was calculated by checking the internal consistency across each item of the BNT and resulted in \( \alpha = .41 \).

#### 2.4.2 | Arithmetic ability

Arithmetic calculation ability was assessed using a similar procedure as Gebuis and van der Smagt (2011) and Lindskog et al. (2017). This test was divided into four subtests (addition, subtraction, multiplication, and division). For each subtest, the participants were presented with a sheet of paper containing printed arithmetic problems of increasing difficulty. For each subtest, they were instructed to complete as many problems as they could within the allotted time of 120 s. A brief pause was included in between each subtest. The
difficulty level of the problems was manipulated by increasing the number of digits or by requiring borrowing or carrying. Each subtest contained 54 problems, except for the division task that contained 27 problems. In sum, the maximum score was 189. The total number of correctly solved arithmetic problems across all four conditions was used as a measure of arithmetic calculation ability. Cronbach’s alpha was calculated by checking the internal consistency across each arithmetic subtest and resulted in $\alpha = .88$. 

2.4.3 | Number sense

Two arrays of blue and yellow dots, ranging from 5 to 21, were displayed on a computer screen. The participant was then asked to determine, as quickly and as accurately as possible, which array contained more dots and press a corresponding color-coded key. The computer software Panamath (v.1.21) was used for this task (see Halberda et al., 2008). The stimulus duration was set at 600 ms for each trial, forcing participants to make approximations. The intertrial interval was self-paced, such that the participant manually pressed a button to summon the next trial. Initially, two practice trials were performed prior to the experimental trials. A total of 162 trials were displayed across four ratios (1.11, 1.18, 1.29, and 2.29). Half the trials were size controlled to minimize confounding perceptual cues. The individual Weber fraction ($w$) was used as a dependent variable. By using arrays with progressively more difficult ratios, the software is able to determine each participant’s $w$ by fitting a psychophysical model to the data as a measure of number sense acuity. Here, lower $w$ indicates a more refined number sense acuity. Split half reliability was $\alpha = .71$. 

2.5 | Procedure

The study was conducted over three sessions in order to avoid fatigue. The first was a computerized survey session containing the administration of the A-DMC, which was filled out at the same time as other participants in a group setting. Then two individual one-on-one sessions with an experimenter at a research lab on the university campus, each lasting about 45 min. All testing was completed within one month during the spring of 2017. Instructions were written in the survey session and read aloud from a printed manuscript during the one-on-one lab sessions. All tests were administered in the same order for all study participants. Computer-based tasks administered during the one-on-one session were run on a laptop, using SuperLab PRO 5. During the first individual lab session, numeracy measures were administered alongside additional questionnaires and tests not relevant for the current paper (e.g., questionnaires regarding personal finance and donating behavior). During the second individual session, the following tasks were administered: RPM, visuospatial task, time perception task, and the EF tasks (nonrelevant tasks regarding emotional processing were also administered during this session).

3 | RESULTS

3.1 | Analytic approach

Prior to data analysis of computerized tasks, intraindividual trials were examined to remove outliers; RTs < 200 ms were removed, as were RTs > 2.5 SD of the individual within a test. For the multiple regression models we verified that, for each model, multicollinearity was not an issue. The variance inflation factor (VIF) was always below 2.11, and tolerance was above .48 for all models. Table 2 provides an overview of all variables and their correlations, including means and standard deviations for all tasks. The first multiple regression analysis used a composite measure of overall decision-making competence as a dependent variable, in which we z-transformed all the scores from each subcomponent of the A-DMC task and then used an unweighted average of all component scores as an overall index of decision-making competence (Bruine de Bruin et al., 2007). Six additional multiple regression models were created, one model corresponding to each A-DMC component. The order in which the blocks were added into the models corresponded to the amount of prior support in the literature indicating them as important predictors of decision-making competence. For each model, we inserted the same four blocks. Age and gender were included as a separate block as control variables, after which general cognitive abilities (e.g., intelligence, EF, and spatial ability) were added in the second block given earlier studies linking EF and intelligence to decision making. The third block consisted of various aspects of numerical skills, and the fourth block consisted of time perception. Time perception was added last as a separate block due to the absence of previous studies on the link between time perception and decision making.

3.2 | Overall decision-making competence

A summary of the multiple regression analysis of the composite score of decision-making competence can be found in Table 3. Age and gender accounted for 9% of the variation in overall decision-making competence, $R^2 = .09, F(2, 179) = 8.93, and p < .001$. Adding a block of general cognitive abilities added an additional 22%, $\Delta R^2 = .22, F_{change} (5, 174) = 11.19, and p < .001$. Adding the numerical block accounted for an additional 5%, $\Delta R^2 = .05, F_{change} (3, 171) = 4.11, and p = .008$. The separate block consisting of time perception added 3% of explained variance, $\Delta R^2 = .03, F_{change} (1, 170) = 8.14, and p = .005$. The complete model explained a total of 39% of the variance, $R^2 = .39, F(11, 170) = 9.78$, and $p < .001$. Analysis of individual predictors of overall decision-making competence is summarized in Table 3. By computing squared part correlations (i.e., semipartial correlations), we can determine the unique variance explained by each individual predictor. Looking at the final model in Step 4, we found that age did not explain any unique variance, whereas gender accounted for 4% unique variance, favoring males. Within the block containing general cognitive abilities, general intelligence contributed 6% unique variance, which was also the strongest predictor of overall decision-
| Tasks                          | M     | SD    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   | 13   | 14   | 15   | 16   | 17   | 18   |
|-------------------------------|-------|-------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 1. Age (in years)             | 24.00 | 3.35  | .20  | .10  | .04  | -.09 | .20  | .10  | .01  | .04  | -.09 | .00  | -.01 | .08  | .05  | .06  | .10  | .04  |
| 2. Gender (1 = male, 0 = female) | -.07  | .90   | -.31 | .11  | .22  | .28  | .13  | .17  | .04  | .05  | .18  | .06  | .01  | .13  | .29  | .31  | -.02 | .00  |
| 3. DMC—overall index          | .00   | .51   | -.43 | .47  | .58  | .42  | .57  | .43  | .08  | -.11 | -.21 | .30  | .39  | .34  | -.21 | .30  |
| 4. DMC—resistance to framing  | 3.42  | .43   | -.12 | .01  | -.09 | .13  | .14  | .24  | .05  | .02  | -.13 | .04  | .12  | .09  | -.13 | .12  |
| 5. DMC—sunk costs             | 4.10  | .67   | -.16 | .06  | .06  | .06  | .17  | .11  | .00  | -.13 | .10  | .18  | .08  | -.12 | .06  |
| 6. DMC—risk perception        | .79   | .11   | -.09 | .31  | .21  | .24  | .10  | -.08 | -.01 | .21  | .23  | .23  | -.13 | .23  |
| 7. DMC—underconfidence/overconfidence | .91   | .06   | -.16 | .06  | .00  | -.21 | .12  | -.02 | -.04 | .08  | .09  | -.09 | .14  |
| 8. DMC—decision rules         | .71   | .21   | -.27 | .41  | .19  | -.27 | -.16 | .41  | .41  | .38  | -.19 | -.19 |
| 9. DMC—social norms           | .61   | .18   | .25  | -.12 | -.20 | .21  | .20  | .17  | .00  | .18  |
| 10. General intelligence (RPM)| 8.81  | 2.44  | -.35 | -.36 | -.23 | .36  | .46  | .45  | -.21 | .21  |
| 11. Visuospatial ability      | 6.95  | 3.70  | -.34 | -.22 | .27  | .30  | .29  | -.23 | .10  |
| 12. EF—switching              | 41.76 | 15.77 | -.38 | -.39 | -.19 | -.47 | .18  | -.22 |
| 13. EF—inhibition             | 25.51 | 5.06  | -.24 | -.20 | -.40 | .12  | -.16 |
| 14. EF—working memory         | 27.71 | 4.51  | -.38 | .48  | -.04 | .23  |
| 15. Numeracy                  | 2.15  | 1.21  | -.49 | -.05 | .07  |
| 16. Arithmetic calculation    | 104.81| 22.78 | -.07 | .21  |
| 17. Number sense (w)          | .16   | .06   | -.24 |
| 18. Time perception           | 69.08 | 6.45  |     |

Note: Significant correlations are in bold (p < .05).
Abbreviations: DMC, Decision-Making Competence; EF, executive function; RPM, Raven's Progressive Matrices.
making competence in our models. Visuospatial ability added an additional 3% unique variance. However, no component of EF explained any further variance significantly. The numerical block contributed significantly as a block, and specifically numeracy (2%) and number sense (2%) explained unique variance. Adding a final block consisting of a singular predictor, time perception, also contributed significantly in explaining unique variance (3%).

### 3.3 Resistance to framing

Recognizing the amount of space required to present the stepwise inclusion of all individual blocks in all the regression analyses, we only present the final models for each subcomponent in Tables 4 and 5 for brevity. The multiple regression analysis of resistance to framing can be found in Table 4. The block containing age and gender did not

| TABLE 3 Hierarchical multiple regression analysis of overall decision-making competence |
|---------------------------------|-------|-------|-------|-------|-------|
| Overall decision-making competence |       |       |       |       |       |
| Step 1 |       |       |       |       |       |
| Age    | .01   | .01   | .62   | .534  | .00   |
| Gender | .29   | .29   | 3.97  | <.001 | .08   |
| Step 2 |       |       |       |       |       |
| Age    | .01   | .07   | 1.08  | .284  | .00   |
| Gender | .27   | .27   | 4.04  | <.001 | .07   |
| General intelligence (RPM) | .09   | .42   | 5.75  | <.001 | .13   |
| Visuospatial ability | −.02  | −.15  | −2.12 | .035  | .02   |
| EF—shifting | .00   | .08   | .99   | .322  | .00   |
| EF—inhibition | −.01 | −.12  | −1.75 | .083  | .01   |
| EF—working memory | .02   | .15   | 2.10  | .037  | .02   |
| Step 3 |       |       |       |       |       |
| Age    | .01   | .08   | 1.30  | .196  | .01   |
| Gender | .22   | .22   | 3.13  | .002  | .04   |
| General intelligence (RPM) | .07   | .33   | 4.26  | <.001 | .07   |
| Visuospatial ability | −.03  | −.19  | −2.74 | .007  | .03   |
| EF—shifting | .00   | .09   | 1.15  | .253  | .01   |
| EF—inhibition | −.01 | −.10  | −1.36 | .176  | .01   |
| EF—working memory | .02   | .13   | 1.77  | .078  | .01   |
| Numeracy | .07   | .16   | 2.06  | .041  | .02   |
| Arithmetic ability | .00   | .03   | .31   | .758  | .00   |
| Number sense (w) | −1.68 | −.19  | −2.86 | .005  | .03   |
| Step 4 |       |       |       |       |       |
| Age    | .01   | .07   | 1.14  | .254  | .00   |
| Gender | .23   | .23   | 3.29  | .001  | .04   |
| General intelligence (RPM) | .06   | .31   | 4.08  | <.001 | .06   |
| Visuospatial ability | −.03  | −.18  | −2.27 | .008  | .03   |
| EF—shifting | .00   | .10   | 1.29  | .197  | .01   |
| EF—inhibition | −.01 | −.09  | −1.27 | .207  | .01   |
| EF—working memory | .01   | .10   | 1.42  | .157  | .01   |
| Numeracy | .07   | .18   | 2.31  | .022  | .02   |
| Arithmetic ability | .00   | .01   | .10   | .919  | .00   |
| Number sense (w) | −1.31 | −.15  | −2.24 | .026  | .02   |
| Time perception | .02   | .18   | 2.85  | .005  | .03   |

Note: $R^2 = .09$ for Step 1 ($p < .001$); $\Delta R^2 = .22$ for Step 2 ($p < .001$); $\Delta R^2 = .07$ for Step 3 ($p = .002$); and $\Delta R^2 = .03$ for Step 4 ($p = .045$).
Abbreviations: EF, executive function; RPM, Raven’s Progressive Matrices.
$^a$ $r^2 =$ squared part correlations (represents the unique contribution for each predictor).
explain any significant variance, $R^2 = .01$, $F(2, 179) = .96$, and $p = .387$. Adding a block of general cognitive abilities explained 8% of the variance, $\Delta R^2 = .08$, $F_{\text{change}}(5, 174) = 3.00$, and $p = .013$. The numerical block was not significant in terms of explaining any variance, $\Delta R^2 = .01$, $F_{\text{change}}(3, 171) = .61$, and $p = .609$. The separate block consisting of time perception did not contribute to the model either, $\Delta R^2 = .01$, $F_{\text{change}}(1, 170) = .86$, and $p = .356$. The complete model explained a total of 10% of the variance, $R^2 = .39$, $F(11, 170) = 1.78$, and $p = .061$. Overview of individual predictors of resistance to framing is summarized in Table 4. The only predictor that was significantly related to resistance to framing was general intelligence, which explained 5% of the variance.

### 3.4 | Resistance to sunk costs

The multiple regression analysis of resistance to sunk costs can be found in Table 4. Age and gender accounted for 7% of the variation in
overall decision-making competence, $R^2 = .07$, $F(2, 179) = 6.38$, and $p = .002$. Adding a block of general cognitive abilities did not add explained variance significantly, $\Delta R^2 = .04$, $F_{change}(5, 174) = 1.61$, and $p = .041$. Adding the numerical block did not add to the model either, $\Delta R^2 = .00$, $F_{change}(3, 171) = 1.30$, and $p = .278$. The block consisting of time perception did not add significantly to the model, $\Delta R^2 = .00$, $F_{change}(1, 170) = .06$, and $p = .813$. The complete model explained a total of $13\%$ of the variance, $R^2 = .13$, $F(11, 170) = 2.27$, and $p = .013$. Analysis of individual predictors of resistance to sunk costs is summarized in Table 4. Looking at the squared part correlations reveals that the only significant predictor is gender, which explain $4\%$ of unique variance. However, one component of EF, inhibition ability, was marginally significant in explaining unique variance (2%, $p = .066$).

### TABLE 5 Hierarchical multiple regression analysis of specific aspects of DMC

|                          | \(B\) | \(\hat{\beta}\) | \(t\)  | \(p\)  | \(pr^2\) |
|--------------------------|-------|------------------|-------|-------|---------|
| **Underconfidence/overconfidence** |       |                  |       |       |         |
| Age                      | .03   | .09              | 1.26  | .209  | .01     |
| Gender                   | .17   | .09              | 1.06  | .290  | .01     |
| General intelligence (RPM) | .00   | .01              | .07   | .942  | .00     |
| Visuospatial ability     | −.07  | −.27             | −3.33 | .001  | .06     |
| EF—shifting              | .01   | .13              | 1.38  | .169  | .01     |
| EF—Inhibition            | −.00  | −.01             | −.136 | .892  | .00     |
| EF—Working memory        | −.02  | −.09             | −1.03 | .303  | .01     |
| Numeracy                 | .09   | .11              | 1.19  | .235  | .01     |
| Arithmetic calculation   | .01   | .15              | 1.41  | .160  | .01     |
| Number sense (w)         | −1.89 | −.11             | −1.41 | .159  | .01     |
| Time perception          | .02   | .14              | 1.85  | .066  | .02     |

| **Application of decision rules** |       |                  |       |       |         |
| Age                      | .01   | .00              | .07   | .946  | .00     |
| Gender                   | .09   | .05              | .62   | .535  | .00     |
| General intelligence (RPM) | .07   | .18              | 2.18  | .031  | .02     |
| Visuospatial ability     | −.02  | −.06             | −.77  | .443  | .00     |
| EF—shifting              | .00   | −.06             | −.78  | .439  | .00     |
| EF—Inhibition            | .01   | .06              | .83   | .408  | .00     |
| EF—Working memory        | .05   | .21              | 2.74  | .007  | .03     |
| Numeracy                 | .16   | .20              | 2.51  | .013  | .02     |
| Arithmetic calculation   | .00   | .00              | .88   | .379  | .00     |
| Number sense (w)         | −2.14 | −.12             | −1.77 | .078  | .01     |
| Time perception          | .00   | .05              | .70   | .484  | .00     |

| **Recognizing social norms** |       |                  |       |       |         |
| Age                      | .01   | .03              | .43   | .671  | .00     |
| Gender                   | .05   | .03              | .31   | .761  | .00     |
| General intelligence (RPM) | .08   | .20              | 2.19  | .030  | .03     |
| Visuospatial ability     | −.04  | −.14             | −1.72 | .087  | .01     |
| EF—shifting              | .00   | −.00             | −.02  | .984  | .00     |
| EF—Inhibition            | −.03  | −.14             | −1.68 | .095  | .01     |
| EF—Working memory        | .02   | .11              | 1.21  | .230  | .01     |
| Numeracy                 | .09   | .10              | 1.16  | .248  | .01     |
| Arithmetic calculation   | .00   | −.07             | −.69  | .489  | .00     |
| Number sense (w)         | 1.04  | .06              | .76   | .449  | .00     |
| Time perception          | .02   | .13              | 1.66  | .099  | .01     |

\(pr^2 = \text{squared part correlations (represents the unique contribution for each predictor).}\)

Abbreviations: DMC, Decision-Making Competence; EF, executive function; RPM, Raven’s Progressive Matrices.
3.5 | Consistency in risk perception

The multiple regression analysis of consistency in risk perception can be found in Table 4. Age and gender accounted for 10% of the variation in consistency in risk perception, $R^2 = .10$, $F(2, 179) = 9.83$, and $p < .001$. Adding a block of general cognitive abilities added an additional 7%, $\Delta R^2 = .07$, $F_{\text{change}} (5, 174) = 2.97$, and $p = .013$. Adding the numerical block did not add to the model, $\Delta R^2 = .02$, $F_{\text{change}} (3, 171) = 1.26$, and $p = .291$. However, the block consisting of time perception added an additional 2% significantly to the model, $\Delta R^2 = .02$, $F_{\text{change}} (1, 170) = 4.58$, and $p = .034$. The complete model explained a total of 21% of the variance, $R^2 = .21$, $F(11, 170) = 4.08$, and $p < .001$. Analysis of individual predictors is summarized in Table 4. Age and gender each explained 3% unique variance, whereas general intelligence explain 2% of unique variance. The only other predictor that was significantly related to risk perception was time perception (2%).

3.6 | Underconfidence/overconfidence

The results from the regression analysis of under/overconfidence aspect of A-DMC can be found in Table 5. The block containing age and gender did not explain any significant variance, $R^2 = .03$, $F(2, 179) = 2.34$, and $p = .100$. Adding a block of general cognitive abilities explained 7% of the variance, $\Delta R^2 = .07$, $F_{\text{change}} (5, 174) = 2.55$, and $p = .030$. The numerical block was only marginally significant in terms of explaining any variance (4%), $\Delta R^2 = .04$, $F_{\text{change}} (3, 171) = 2.41$, and $p = .069$. The separate block consisting of time perception also made a marginally significant contribution to the model (2%), $\Delta R^2 = .02$, $F_{\text{change}} (1, 170) = 3.42$, and $p = .066$. The complete model explained a total of 15% of the variance, $R^2 = .15$, $F(11, 170) = 2.64$, and $p = .004$. Overview of individual predictors of under/overconfidence is summarized in Table 5. No cognitive predictors explained any unique variance except for visuospatial ability, which was negatively associated with under/overconfidence (6%). Time perception was marginally significant as a predictor ($p = .066$) and contributed with 2% unique variance explained.

3.7 | Application of decision rules

In Table 5, the regression analysis of application of decision rules component can be found. The block containing age and gender did not explain any significant variance, $R^2 = .03$, $F(2, 179) = 2.32$, and $p = .101$. Adding a block of general cognitive abilities explained 24% of the variance, $\Delta R^2 = .24$, $F_{\text{change}} (5, 174) = 11.08$, and $p < .001$. The numerical block also contributed significantly (5%) in terms of explaining any variance, $\Delta R^2 = .05$, $F_{\text{change}} (3, 171) = 3.88$, and $p = .010$. The block consisting of time perception did not explain any variance, $\Delta R^2 = .00$, $F_{\text{change}} (1, 170) = .49$, and $p = .484$. The complete model explained a total of 31% of the variance, $R^2 = .31$, $F(11, 170) = 6.94$, and $p < .001$. Overview of individual predictors of application of decision rules is summarized in Table 5. The strongest predictors were general intelligence (2%), WM capacity (3%), and numeracy (3%).

3.8 | Recognizing social norms

The regression models of recognizing social norms can be found in Table 5. Age and gender did not explain any significant variance, $R^2 = .00$, $F(2, 179) = .20$, and $p = .817$. The block containing general cognitive abilities explained 11% of the variance, $\Delta R^2 = .11$, $F_{\text{change}} (5, 174) = 4.21$, and $p = .001$. The numerical block did not add significant variance, $\Delta R^2 = .01$, $F_{\text{change}} (3, 171) = .45$, and $p = .716$. The block consisting of time perception did not explain any variance either, $\Delta R^2 = .01$, $F_{\text{change}} (1, 170) = 2.75$, and $p = .099$. The complete model explained a total of 31% of the variance, $R^2 = .31$, $F(11, 170) = 2.33$, and $p = .011$. An overview of individual predictors of application of recognizing social norms is provided in Table 5. The only cognitive ability that predicted this component of the A-DMC scale was general intelligence (3%).

4 | DISCUSSION

Our objective was to investigate which cognitive abilities that support decision-making competence in adults. By using a comprehensive test battery of cognitive abilities, our hierarchical multiple regression analyses enabled us to carefully control for previously known predictors and control variables while evaluating the impact of hitherto unexplored, but potentially important, variables of interest.

Regarding the overall decision-making competence, consisting of a composite score of the individual components of the A-DMC, the strongest predictor was general intelligence (RAPM). This was in line with our initial expectation and corroborates earlier studies by Bruine de Bruin et al. (2007) and Del Missier et al. (2012). Thus, we reinforce the notion that successful decision making is bolstered by having the ability to reason about cognitively complex information, irrespective of domain.

What was perhaps more interesting, however, was to examine which, if any, other cognitive abilities would predict overall decision-making competence once including general intelligence in our models. Earlier research by Del Missier et al. (2012) found that EF could explain additional variance above and beyond general intelligence. However, we failed to find a significant contribution of any EF component to overall decision-making competence. Although the WM component was a significant predictor in Step 2 of the analysis (see Table 3), this contribution disappeared once we included the numerical block of predictors. Thus, it seems that the combination of numerical abilities and visuospatial abilities outcompeted WM ability in the final model, which also highlights the importance of utilizing comprehensive test batteries such as the one in the current study. Still, WM was the strongest predictor of “application of decision-rules” component as predicted, which is in line with Del Missier et al. (2012). WM
likely ties into this aspect of A-DMC insofar as having a greater WM capacity will allow an individual to keep more information active in a mental workspace, thus supporting effective application of decision rules.

We also explored whether the order in which we inserted the predictors could be a factor. Therefore, explored whether putting the EF measures first before any other cognitive variables would change our models. However, this had no impact on the results (see Tables S6–S8). Considering the fact that one can use different measures of the trailmaking task and Stroop task, we also performed exploratory post hoc analyses of derived difference and ratio scores of the trailmaking test and Stroop task as opposed to the absolute response times (see Arbuthnott & Frank, 2000; Salthouse, 2011; Sánchez-Cubillo et al., 2009, for discussions on which indices to use). Using difference scores (e.g., B–A in the trailmaking task and congruent color condition time subtracted from the incongruent condition) revealed no change in results (see Tables S1–S3). Including ratio scores (e.g., B:A) showed that switching component of EF was related to overall DMC index, but no subcomponent of A-DMC. The Stroop ratio score was significantly predictive of “applying decision rules” component of the A-DMC, but all other results remained the same (see Tables S1–S5). These post hoc analyses should be interpreted with caution given that our a priori decision was to use the absolute scores on the trailmaking task and the Stroop task in order to account for the speed and efficiency with which one can switch between aspects and inhibit irrelevant responses. Taken together, the overall pattern of our data suggests that EF are still important factors of DMC, although the extent to which should be further investigated, but that other predictors could be potentially be even more important.

Considering the role of visuospatial cognitive processing, as indexed using a mental rotation task, it is likely that visual and spatial aspects of WM are critical elements in our observed association with decision-making competence. By examining the numerical block of predictors that targeted slightly different aspects of mathematical competency, we observe that being able to rapidly solve arithmetical problems did not predict decision-making competence. Although raw calculation efficiency using numerical information proved not to be important, the ability to reason and solve more complex problems containing numerical information was (i.e., numeracy). This corroborates studies on normative decision making (Cavanaugh et al., 2008; Peters et al., 2006; Sinayev & Peters, 2015). One caveat, however, is that the arithmetic calculation task and the numeracy task involve different levels of time pressure in terms of time required per item. This could result in different levels of perceived stress on these task that could impact performance unevenly.

Therefore, our study reinforces the preexisting notion that numeracy is indeed important for decision-making competence. Individuals with higher numeracy likely decode numerical information faster, but more importantly, these individuals can apply correct mathematical concepts and procedures and make judgments about which parts of numerical information are pertinent to the situation at hand. The link between numeracy and normative decision making involving numerical information is uncontroversial, but some argue that numeracy is tied to nonnumerical decision making as well (Cokely et al., 2018). Numeracy has been suggested to relate to judgment of social relationships, behavioral norms, health behaviors, among others (Cokely et al., 2018). Although numeracy was primarily related to “application of decision rules,” which involves numbers, our current results support the idea that numeracy assists decision making beyond the numerical domain. Interestingly, numeracy predicted decision-making competence even when general intelligence was included in the model, which demonstrates a demarcation between these two constructs. Considering the mounting evidence showing a strong correlation, depending on the population and measures used, between general intelligence and numeracy (r’s mainly ranging from .37–.61; e.g., Cokely et al., 2012; Bruine de Bruin et al., 2007; Dieckmann et al., 2015; Sobkow et al., 2020) our current results reinforce the notion that these abilities and skills contribute to decision making independently of each other. Still, when considering the unique contributions of each predictor, as indexed by the squared part correlations, general intelligence is a stronger predictor than numeracy. The prominent role of general intelligence vis-à-vis numeracy is also reflected by the fact that intelligence was related to four out six individual components of the A-DMC, which is in stark contrast to the numeracy measure that was related primarily to the “application of decision rules.”

To further investigate the roles of numeracy and general intelligence, we performed exploratory post hoc regression analyses in order to disentangle the relative role of each predictor. Given that we inserted a block of general cognitive abilities prior to inserting a block containing numerical predictors, we were aware of the fact that general intelligence may have explained common and unique variance that the numeracy question would explain as well. Therefore, we reversed the order of the blocks, such that the numerical block was inserted first and the general cognitive block inserted afterward. Nevertheless, the results remained identical to our initial models, where numeracy showed a $r^2 = .02$ ($\beta = .18$) and general intelligence showed $r^2 = .06$ ($\beta = .31$). Thus, the results indicate that general intelligence shows a stronger link to overall decision-making competence, both in terms of beta values and squared part correlations, than numeracy, which goes against Cokely et al. (2018). We further investigated the relationship between numeracy, intelligence, and decision-making competence through a series of mediation analyses to fully see whether one predictor was fully mediated by another. However, we found both significant direct and indirect effects of numeracy and intelligence on decision-making competence, regardless of whether the predictors were assigned as the independent or mediating variable. For brevity, we refer to supporting information (see Figure S1) for further details on the mediation analyses. We therefore conclude that both numeracy and intelligence have an independent impact on decision-making competence.

The last component of the numerical skills that we included in our models was the measure of the innate number sense (Dehaene, 2011;...
Halberda et al., 2008). The number sense allows humans to estimate quantities and constitute a system for semantic representation of numerosity. The number sense is responsible for representing large and approximate numbers via a logarithmic analog mental number line that is inherently noisy (Dehaene, 2011; Feigenson et al., 2004). Therefore, the ability to discriminate between sets of objects is ratio dependent (Halberda et al., 2008) and would most likely be a subcomponent in the construct of numeracy given that numeracy itself concerned with the ability to reason about probabilities and fractions (Cokely et al., 2012). But the direct relationship to decision-making skills has remained unexplored. Our results indicate that number sense is not related to any specific aspect of the A-DMC. Interestingly, however, it was significantly predictive of overall decision-making competence ($\beta = -0.15, pr^2 = 0.02$), which is very similar to the effect of numerosity on A-DMC. The mechanism by which number sense operates on decision making is unknown, but a tentative interpretation is that having a more refined number sense allows one to make accurate, intuitive estimations of quantities and probabilities in many areas of everyday life. The ability to discriminate between sets of objects, the number sense, is ratio dependent and obey psychophysical laws, such as Weber’s law (Halberda et al., 2008). As such, it is conceptually plausible that the number sense constitutes a component of the construct of numeracy, given that numeracy itself is concerned with the ability to reason about probabilities and fractions (Cokely et al., 2012). Nevertheless, it is interesting that the number sense predicts decision-making competence concurrently with numeracy in our models.

The final ability that we investigated was time perception ability. Time management is a pertinent aspect of decision making where the temporal discounting of various choices has to be taken into account (Frederick et al., 2002), but no previous study has investigated whether the specific ability to perceive time is related to sound decision making. It stands to reason that an accurate representation of time would be beneficial for navigating in a decision-making landscape, where both accurate and timely decisions have to be made. We inserted this predictor last in our models in order to be as conservative as possible and to investigate the specificity with which it could predict decision-making competence. Despite this conservative approach, we found that time perception ability predicted overall decision-making competence and was related to two specific aspects of the A-DMC components. In fact, time perception ability was a stronger predictor than both number sense and numeracy ($\beta = 0.18, pr^2 = 0.03$), thus being outperformed only by general intelligence out of all predictors. Moreover, time perception as a construct has been linked to other cognitive abilities, such as WM capacity (Mioni et al., 2017). Supra-second intervals, especially at the higher end of the temporal spectrum, would place a significant load on WM resources. Indeed, supra-second temporal processing activates prefrontal areas of the brain (Wittmann, 2009), which in turn are cortical loci for spatial WM processing together with connecting areas in parietal regions (Rotzer et al., 2009; Rubinsten & Henik, 2009). It is therefore notable that time perception ability was a significant predictor, despite including WM capacity and other EFs in the models. How can time perception ability bolster decision making? A plausible mechanism is that time perception ability relates to temporal discounting and self-regulation, such that individuals with well-developed time perception assign value functions to decisions that favor long-term intertemporal choice. Also, work by Todrov et al. has suggested the importance of spatial and temporal processing in successful everyday multitasking performance (Todrov et al., 2018) and that the coordination of several tasks requires time-to-space transformational processes (Mäntylä et al., 2017). The coordination of everyday multitasking was suggested to be reliant upon temporal coordination of activities, where the representation and planning of these activities can spatially represent to enhance performance (Mäntylä et al., 2017). This interpretation could unify our findings where both temporal processing and spatial processing are linked to DMC. Therefore, a novel contribution of this study is establishing that temporal and spatial processing is also tied to scores on the A-DMC. The link between ability and intertemporal choice remains to be empirically investigated, however.

Limitations of the current research include the restricted way of measuring cognitive abilities. For any specific cognitive ability, there are several viable tools that can be employed in order to assess these abilities. For instance, we used three instruments to measure the three respective EF, and although these are validated and conventional assessment tools, one could have substituted them in favor of other measures of EF. One could utilize another WM task specifically targeting the updating component of WM and use more than one indicator to assess each facet of EF to overcome task impurity and other measurement problems. Therefore, we cannot make definitive claims about EF and the relationship with DMC, given the observed absence of an effect, but our results nevertheless provide support for the importance of auxiliary processes beyond EF. It is also worth noting that all predictors in our models are quite modest in terms of their explained variance, joint as well as unique. This also ties into another limitation, although by design, which is the sole focus on cognitive abilities. Decision-making competence is a multifaceted construct that is related to, among others, personality variables (e.g., introversion) and decision-making styles (e.g., brooding about decisions). In a recent paper by Bruine de Bruin et al. (2020), the authors suggested that emotion regulation and motivation are important psychological processes that complement general cognitive abilities in making sound decisions. Moreover, the authors underscore that certain decision-making components may be subject to change throughout ontogeny, such that some aspects become weaker as a function of age (e.g., fluid intelligence). The upside is that that a potential mapping of which psychological constructs are linked to each specific component of A-DMC could inform how we can home in and implement targeted interventions to mitigate those adverse effects. Thus, future studies should also juxtapose cognitive abilities with other potentially important variables. The correlational nature of the current study highlights the need to investigate the causal role of DMC and cognitive abilities using other research designs. Longitudinal or
prospective designs could be used for example, by administering measures of cognitive abilities in children and follow up a number of years later to measure DMC as well as decision making outcomes.

Another limitation of our study is that the study sample consisted of university students who likely are homogenous in terms of their socioeconomic status and overall cognitive abilities and decision making. Additional research using more representative samples across a wider age range could provide data with more variance, and thus perhaps a more comprehensive picture of which cognitive abilities are important for decision making. Utilizing a larger sample could also prove beneficial in detecting small effects and contributions of specific cognitive abilities.

Taken together, our main findings from administering a comprehensive test battery of cognitive abilities are threefold. First, we reinforce the important role that general intelligence plays in decision-making competence and that numeracy and intelligence show independent contributions. Second, EFs, which have been tied to A-DMC scores in previous research (e.g., Del Missier et al., 2012), did not contribute to superior decision-making competence once numerical, temporal, and spatial abilities were included in the models. Third, a novel finding is that time perception was tied to superior decision-making competence, which invites further research into exactly how this ability relates to decision-making competence. Overall, this study extends previous work by Del Missier et al. (2012) and related research probing which cognitive abilities matter for successful decision making.

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REFERENCES
Arbuthnott, K., & Frank, J. (2000). Trail making test, Part B as a measure of executive control: Validation using a set-switching paradigm. Journal of Clinical and Experimental Neuropsychology, 22(4), 518–528. https://doi.org/10.1076/jcen-3395(200008)22:4:1-0:FTS18
Arkes, H. R., & Blumer, C. (1985). The psychology of sunk cost. Organizational Behavior and Human Decision Processes, 35(1), 124–140. https://doi.org/10.1016/0749-5978(85)90049-4
Ballinger, T. P., Hudson, E., Karkoviata, L., & Wilcox, N. T. (2011). Saving behavior and cognitive abilities. Experimental Economics, 14, 349–374. https://doi.org/10.1007/s10683-010-9271-3
Basile, A. G., & Toplak, M. E. (2015). Four converging measures of temporal discounting and their relationships with intelligence, executive functions, thinking dispositions, and behavioral outcomes. Frontiers in Psychology, 6, 728.
Baudic, S., Dalla Barba, G., Thibaudet, M. C., Smaghe, A., Remy, P., & Traykov, L. (2006). Executive function deficits in early Alzheimer’s disease and their relations with episodic memory. Archives of Clinical Neuropsychology, 21(1), 15–21.
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
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, 29(2), 186–192. https://doi.org/10.1177/0963721420915092
Burks, S. V., Carpenter, J. P., Goette, L., & Rustichini, A. (2009). Cognitive skills affect economic preferences, strategic behavior, and job attachment. Proceedings of the National Academy of Sciences of the United States of America, 106(19), 7745–7750. https://doi.org/10.1073/pnas.0812360106
Carroll, J. B. (1993). Human cognitive abilities: A survey of factor-analytic studies. New York, NY, USA: Cambridge University Press.
Cattell, R. B. (1963). Theory of fluid and crystallized intelligence: A critical experiment. Journal of Educational Psychology, 54(1), 1–22. https://doi.org/10.1037/h0046743
Cavanaugh, K., Huizinga, M. M., Wallston, K. A., Gebretsadik, T., Shintani, A., Davis, D., Gregory, R. P., Fuchs, L., Malone, R., Cherrington, A., Pignone, M., DeWalt, D. A., Elasy, T. A., & Rothman, R. L. (2008). Association of numeracy and diabetes control. Annals of Internal Medicine, 148(10), 737–746. https://doi.org/10.7326/0003-4819-148-10-200805200-00006
Church, R. M. (1984). Properties of the internal clock. Annals of the New York Academy of Sciences, 423(1), 566–582. https://doi.org/10.1111/j.1749-6632.1984.tb23459.x
Cohen, J. E. (1988). Statistical power analysis for the behavioral sciences (2nd ed.). Routledge: New York.
Cokely, E. T., Feltz, A., Ghazal, S., Allan, J. N., Petrova, D., & Garcia-Retamero, R. (2018). Decision making skills: From intelligence to numeracy and expertise. In K. A. Ericsson, R. R. Hoffman, A. Kozbelt, & A. M. Williams (Eds.), Cambridge handbook of expertise and expert performance (2nd ed.). New York, NY: 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
Dehaene, S. (2011). The number sense. New York, NY: Oxford University Press.
Del Missier, F., 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/10.1080/13546781003631117
Del Missier, F., 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
Del Missier, F., Mäntylä, T., Hansson, P., Bruine de Bruin, W., Parker, A. M., & Nilsson, L.-G. (2013). The multifold relationship of numerical and intelligence ability and decision-making competence. Frontiers in Psychology, 4, 211. https://doi.org/10.3389/fpsyg.2013.00211
Dewberry, C., Juanchich, M., & Narendran, S. (2013). The latent structure of decision styles. Personality and Individual Differences, 54(5), 566–571. https://doi.org/10.1016/j.paid.2012.11.002
Raven, J. C., Court, J. H., & Raven, J. (1988). Manual for Raven’s progressive matrices and vocabulary scales (Section 4). London: H. K. Lewis.

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

Román, F. J., Colom, R., Hillman, C. H., Kramer, A. F., Cohen, N. J., & Barbay, A. K. (2019). Cognitive and neural architecture of decision making competence. NeuroImage, 199, 172–183. https://doi.org/10.1016/j.neuroimage.2019.05.076

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 for decision rules? Aging, Neuropsychology, and Cognition, 26(2), 174–189. https://doi.org/10.1080/13825585.2017.1418283

Rotzer, S., Loenneker, T., Kucian, K., Martin, E., Klaver, P., & von Aster, M. (2009). Dysfunctional neural network of spatial working memory contributes to developmental dyscalculia. Neuropsychologia, 47, 2859–2865. https://doi.org/10.1016/j.neuropsychologia.2009.06.009

Rousselle, L., & Noël, M. P. (2007). Basic numerical skills in children with mathematics learning disabilities: A comparison of symbolic vs non-symbolic number magnitude processing. Cognition, 102, 361–395. https://doi.org/10.1016/j.cognition.2006.01.005

Rubinsteini, O., & Henik, A. (2009). Developmental dyscalculia: Heterogeneity might not mean different mechanisms. Trends in Cognitive Sciences, 13(2), 92–99. https://doi.org/10.1016/j.tics.2008.11.002

Salthouse, T. (2011). What cognitive abilities are involved in trail-making performance? Intelligence, 39(4), 222–232. https://doi.org/10.1016/j.intell.2011.03.001

Sánchez-Cubillo, I., Periáñez, J. A., Adrover-Roig, D., Rodriguez-Sánchez, J. M., Rios-Lago, M., Triapu, J., & Barceló, F. (2009). Construct validity of the Trail Making Test: Role of task-switching, working memory, inhibition/interference control, and visuomotor abilities. Journal of the International Neuropsychological Society, 15, 438–450. https://doi.org/10.1016/j.jins.2009.09.062

Schley, D. R., & Peters, E. (2014). Assessing “economic value”: Symbolic-number mappings predict risky and riskless valuations. Psychological Science, 25(3), 753–761. https://doi.org/10.1177/0956797613514585

Schwarz, 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), 966–972. https://doi.org/10.7326/0003-4819-127-11-199712010-00003

Shepard, R. N., & Metzler, J. (1971). Mental rotation of three-dimensional objects. Science, 701–703.

Sherman, L. E., Rudie, J. D., Pfeifer, J. H., Masten, C. L., McNealy, K., & Dapretto, M. (2014). Development of the default mode and central executive networks across early adolescence: A longitudinal study. Developmental Cognitive Neuroscience, 10, 148–159.

Sinayev, A., & Peters, E. (2015). Cognitive reflection vs. calculation in decision making. Frontiers in Psychology, 6, 532.

Skagerlund, K., & Träff, U. (2014). Development of magnitude processing children with developmental dyscalculia: Space, time, and number. Frontiers in Psychology, 5, 675.

Sokkow, A., Olszewka, 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

Strömberg, C., Skagerlund, K., Västfjäll, D., & Tínghög, G. (2020). Subjective self-control but not objective measures of executive functions predicts financial behavior and well-being. Journal of Behavioral and Experimental Finance, 27, 1–7.

Todorov, I., Kubik, V., Carelli, M. G., Del Missier, F., & Mäntylä, T. (2018). Spatial offloading in multiple task monitoring. Journal of Cognitive Psychology, 30(2), 230–241. https://doi.org/10.1080/20445911.2018.1436551

Tversky, A., & Kahneman, D. (1981). The framing of decisions and the psychology of choice. Science, 211(4481), 453–458. https://doi.org/10.1126/science.7455683

van der Sluis, S., de Jong, P. F., & van der Leij, A. (2004). Inhibition and shifting in children with learning deficits in arithmetic and reading. Journal of Experimental Child Psychology, 87, 239–266. https://doi.org/10.1016/j.jecp.2003.12.002

Vandenberg, S. G., & Kuse, A. R. (1978). Mental rotations: A group test of three-dimensional spatial visualization. Perceptual and Motor Skills, 47, 599–604.

Verdine, B. N., Irwin, C. M., Golinkoff, R. M., & Hirsh-Pasek, K. (2014). Contributions of executive function and spatial skills to preschool mathematics achievement. Journal of Experimental Child Psychology, 126, 37–51. https://doi.org/10.1016/j.jecp.2014.02.012

Wai, J., Lubinski, D., & Benbow, C. P. (2009). Spatial ability for STEM domains: Aligning over 50 years of cumulative psychological knowledge solidifies its importance. Journal of Educational Psychology, 101(4), 817–835. https://doi.org/10.1037/a0016127

Wechsler, D. (2008). Wechsler Adult Intelligence Scale (4th ed.). San Antonio, TX: Pearson Assessment.

Weller, J., Ceschi, A., Hirsh, L., Sartori, R., & Constantini, A. (2018). Accounting for individual differences in decision-making competence: Personality and gender differences. Frontiers in Psychology, 9, 2258. https://doi.org/10.3389/fpsyg.2018.02258

Wittmann, M. (2009). The inner experience of time. Philosophical Transactions of the Royal Society B, 364, 1955–1967. https://doi.org/10.1098/rstb.2009.0003

Wittmann, M., & Paulus, M. P. (2008). Decision making, impulsivity and time perception. Trends in Cognitive Sciences, 12(1), 7–12. https://doi.org/10.1016/j.tics.2007.10.004

Wittmann, M., & van Wassenhove, V. (2009). The experience of time: Neural mechanisms and the interplay of emotion, cognition and embodiment. Philosophical Transactions of the Royal Society B, 364, 1809–1813. https://doi.org/10.1098/rstb.2009.0025

Woloshin, S., Schwartz, L. M., Black, W. C., & Welch, H. G. (1999). Women’s perceptions of breast cancer risk: How you ask matters. Medical Decision Making, 19(3), 221–229. https://doi.org/10.1177/0272989X9901900301

Zauberman, G., Kim, B. K., Malkoc, S. A., & Bettman, J. R. (2009). Discounting time and time discounting: Subjective time perception and Intertemporal preferences. Journal of Marketing Research, 46(4), 543–556. https://doi.org/10.1509/jmkr.46.4.543

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