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Cognitive and neural architecture of decision making competence

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A B S T R A C T

Although cognitive neuroscience has made remarkable progress in understanding the neural foundations of goal-directed behavior and decision making, neuroscience research on *decision making competence*, the capacity to resist biases in human judgment and decision making, remain to be established. Here, we investigated the cognitive and neural mechanisms of decision making competence in 283 healthy young adults. We administered the Adult Decision Making Competence battery to assess the respondent's capacity to resist standard biases in decision making, including: (1) resistance to framing, (2) recognizing social norms, (3) over/under confidence, (4) applying decision rules, (5) consistency in risk perception, and (6) resistance to sunk costs. Decision making competence was assessed in relation to core facets of intelligence, including measures of crystallized intelligence (Shipley Vocabulary), fluid intelligence (Figure Series), and logical reasoning (LSAT). Structural equation modeling was applied to examine the relationship(s) between each cognitive domain, followed by an investigation of their association with individual differences in cortical thickness, cortical surface area, and cortical gray matter volume as measured by high-resolution structural MRI. The results suggest that: (i) decision making competence is associated with cognitive operations for logical reasoning, and (ii) these convergent processes are associated with individual differences within cortical regions that are widely implicated in cognitive control (left dACC) and social decision making (right superior temporal sulcus; STS). Our findings motivate an integrative framework for understanding the neural mechanisms of decision making competence, suggesting that individual differences in the cortical surface area of left dACC and right STS are associated with the capacity to overcome decision biases and exhibit competence in decision making.

1. Introduction

Cognitive neuroscience has made significant progress in understanding the neural mechanisms that enable adaptive behavior and decision making (for a review, see (Heilbronner and Hayden, 2016)). For example, considerable research demonstrates that the dorsal anterior cingulate cortex (dACC) supports cognitive operations for monitoring, controlling, and evaluating choice behavior. Early evidence from event-related potential (ERP) studies demonstrated that the dACC generates an error monitoring signal, supporting its role in the detection and monitoring of conflict (Falkenstein, 1990). Later research established a broader perspective, providing evidence that the dACC generates control (Johnston et al., 2007) and economic (Wallis and Rich, 2011) signals for which error monitoring represents a special case. From this perspective, the detection of conflict initiates control signals in the dACC to facilitate adaptive behavior and decision making (Botvinick et al., 2001). In the context of economic decision making, signals in the dACC facilitate the evaluation and comparison of rewards (Wallis and Rich, 2011). Researchers have increasingly advocated for a comprehensive theory of dACC function, replacing the concept of conflict monitoring with a broader capacity for representing the expected value of control (Shenhav et al., 2013). According to this framework, the dACC integrates information about the expected payoff from a controlled process, along with the amount of control required to achieve the payoff and the associated cognitive effort or cost. Thus, by monitoring control-relevant information and estimating the expected value of control, the dACC is believed to guide the optimization of choice and the selection of new strategies for adaptive behavior and decision making.

Accumulating evidence has broadened the scope of research investigating the neural mechanisms of decision making to assess contributions

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from social and emotional information processing regions. Indeed, evidence from the social cognitive neuroscience literature indicates that decision making engages regions that are known to support social information processing, including the posterior superior temporal sulcus (STS). This region is believed to support our ability to understand the nature of social interactions (e.g., recognition of individual agents and their actions, group membership, etc.) and to provide important information about how to navigate the social world (e.g., informing whether we should engage in cooperation versus competition). Evidence indicates that this region selectively responds when viewing social interactions between two agents (Isik et al., 2017) and is known to support moral judgment and decision making, particularly in the context of emotionally engaging moral dilemmas (Green et al., 2001, 2002; Moll et al., 2002).

Although an extensive neuroscience literature examines the neural mechanisms of decision making, applications to the study of human judgment and decision making using measures from the psychological literature remain to be investigated. A wealth of psychological evidence demonstrates that human judgment and decision making reflects the operation of heuristics that reduce the complexity of the problem and, as a consequence, introduce systematic biases in decision making (for a review see (Gilovich et al., 2002). Thus, accurate decision making often depends on the capacity to monitor intuitive, heuristic processes and to deploy cognitive control mechanisms that override the intuitive response in favor of reasoning from critical thought and evaluation. This capacity for cognitive control provides the foundation for competence in decision making, reflecting mechanisms for the adaptive regulation and control of highly-accessible, intuitive responses that promote biases in decision making.

Indeed, decades of research in the human judgment and decision making literature have established core competencies of decision making, which are captured by the Adult Decision Making Competence Battery (A-DMC (Bruine de Bruin et al., 2007)). The A-DMC is a well-validated test of decision making competence, whose measures demonstrate internal consistency, high test-retest reliability, and are predictive of real-world decision making, including economic, social, and medical choices (Bruine de Bruin et al., 2007). The A-DMC examines three essential competencies of decision making, including: (i) *comprehension*, the capacity to assess the likelihood and value of possible actions and their consequences; (ii) *integration*, the ability to combine available information to make an adaptive choice; and (iii) *meta-cognitive awareness*, the capacity to use analysis and deliberation to evaluate intuitive responses, mental operations, and overt behaviors in decision making. A comprehensive assessment of the respondent's capacity to demonstrate these key facets of decision making is provided by an overall *decision making competence* score, which represents the capacity to overcome well-established decision biases and to demonstrate competence in decision making.

Research investigating the neural foundations of goal-directed behavior and the complementary psychological literature on the essential role of cognitive control mechanisms in decision making competence together motivate the present study, which aims to integrate research across these largely independent disciplines by elucidating the neural mechanisms of decision making competence. The present exploratory study therefore aimed to investigate whether performance on the A-DMC is associated with individual differences in cortical thickness, cortical surface area, and cortical gray matter volume as measured by high-resolution structural MRI in a large sample of 282 healthy young adults.

Surface-Based Morphometric (SBM) methodology was used to compute the structural MRI features. Cortical thickness is related to the number of cells within a given column, cortical surface area is related to the degree of folding, while cortical gray matter volume combines both indices (Chklovskii et al., 2004; la Fougere et al., 2011; Thompson et al., 2007). Previous research explored the association between individual differences in structural MRI indices and high-level cognitive functions (e.g., intelligence, Basten et al., 2015; perception, Duncan and Boynton, 2003, memory, Van Petten, 2004; attention, Valera et al., 2007; meta-cognition, Buchy et al., 2015; see Kanai and Rees, 2011). However, the contributions of structural MRI features to the decision making literature remain to be investigated. We therefore conducted a whole-brain, exploratory analysis that examined multiple structural MRI measures (i.e., cortical thickness, cortical surface area, and cortical gray matter volume) in an effort to assess whether performance on the A-DMC was associated with regions that have been widely implicated in the neuroscience literature on decision making (e.g., dACC).

In addition, we sought to characterize the relationship between decision making competence and multiple measures of intelligence, applying structural equation modeling (SEM) to assess associations with performance on tests of crystallized intelligence (Shipley Vocabulary), fluid intelligence (Figure Series), and logical reasoning (LSAT). To further isolate the neural mechanisms associated with decision making competence – beyond closely related processes for fluid cognition – we examined the unique contributions of cortical regions to decision making competence while controlling for performance on tests of fluid intelligence. Finally, we examined the specific cognitive operations underlying the observed A-DMC sensitive regions with respect to the six subtests of the A-DMC, providing SEM evidence to further elucidate the neural architecture of specific facets of decision making competence.

2. Methods

2.1. Participants

The experimental protocol was approved by the University of Illinois Institutional Review Board (IRB). Study participants were recruited from the Urbana-Champaign, Illinois community and provided informed written consent in accordance with the University of Illinois IRB. Study eligibility required participants to: (a) be 18–44 years of age; (b) have at least a high school diploma; (c) speak English fluently; (d) have normal or corrected-to-normal vision and hearing; (e) not have current or recent medications affecting the central nervous system; (f) not have a history of psychological, neurological, or endocrine disease; (g) not have had a concussion within the past two years; (h) not have learning disorders; (i) to not smoke more than 10 cigarettes per day; (j) to have a body mass index under 35; and (k) to have at least one positive response on the revised Physical Activity Readiness Questionnaire (Thomas et al., 1992).

The present study examines participants ($n = 300$) for whom complete structural MRI (T1-weighted sequence) and cognitive data (A-DMC, Shipley Vocabulary, Figure Series, and LSAT) were acquired. Seventeen participants failed to pass quality control performed after processing the T1-weighted images with the CIVET pipeline, and consequently, were removed from the final analysis. Therefore, the present study is comprised of 283 participants (147 females, mean age = 23.32, $SD = 5.07$). The highest education level achieved in this sample reflected the following distribution: High school graduate ($n = 26$, 9.2%); Some college ($n = 146$, 51.6%); College graduate ($n = 50$, 17.7%); Some postgraduate ($n = 26$, 9.2%) and Master's degree or higher ($n = 35$, 12.4%).

2.2. Psychological assessment

A comprehensive battery of cognitive tests was administered in the present study, including measures of decision making competence, crystallized intelligence, fluid intelligence, and logical reasoning. We review the administered battery of tests in further detail below.

2.3. Adult decision-making competence (A-DMC)

We administered a well-validated battery of measures to investigate six facets of decision making, employing the Adult Decision Making Competence test (Bruine de Bruin et al., 2007). As we review below, a confirmatory factor analysis (CFA) was performed to obtain a decision making competence index based on the six subtests of the A-DMC. A description of each subtest is presented below.

Resistance to framing. Resistance to framing measures the extent to which a positive or negative framing of a problem can influence the evaluation of an outcome. Problems are either of a risky-choice or attribute type. Each participant saw pairs of questions that differed only in the positive or negative framing. For instance, suppose 1200 endangered animals are threatened by a pesticide. The positive frame requires a choice between saving 600 animals for sure OR a 75% chance that 800 animals will be saved and a 25% chance that 0 animals will be saved. The negative frame is identical, except saving/saved becomes losing/lost.

Recognizing social norms. Recognizing social norms measures how well a participant assesses social norms. There are two parts to each question. First, the respondent chooses from a binary response option for what they believe is socially acceptable. For instance, 'Do you think it is sometimes okay to steal under certain circumstances?'. The second part asks, 'Out of 100 age similar peers, how many would also find that behavior acceptable?' The responses from all participants are aggregated from the first part of each question, providing an estimate of the percentage of respondents from the entire sample who endorsed the behavior.

Over/Under confidence. Over/under confidence measures the extent to which a participant recognizes the limits of their knowledge. A respondent first provides a true or false response to a question. Then the respondent is asked to quantify their confidence in their true or false response by rating that answer on a scale from 50% (just guessing) to 100% (absolutely sure).

Applying decision rules. Applying decision rules asks respondents to use different types of decision rules: elimination by aspects, satisficing, lexicographic, or equal weights. Each question has a set of consumer priorities and a set of product options under consideration by the decision-maker. Respondents select one answer from a set of multiple choice options.

Consistency in risk perception. Consistency in risk perception measures how well a participant adheres to probability rules. The participant scores the likelihood of an event happening to them on a scale between 0% (no chance) and 100% (certain). There are three dimensions manipulated to evaluate the respondent's ability in assessing probability: time, complementariness and relational status (in set theoretic terms). For the time dimension, events are judged on their likelihood of happening in the next year or within five years. The one and five-year judgments by the participant are two separate items; but the pair is scored for the test as correct if the event happening in one year has a probability less than or equal to the event happening in five years. A complementary event is defined as one minus the probability of the event happening. For this dimension, there are two parts to each question, such as the probability of getting into an accident while driving and the probability of being accident free, and the probabilities assigned must sum to 1. The final dimension also contains two parts, a subset and superset event. If the superset event is the probability of death from any cause, then one possible subset event is the probability of death from a terrorist attack. Since the latter is a subset of the former, the latter must have a probability no larger than the former. If a respondent provides a response consistent with these set theoretic rules, then the item is scored as correct for this subtest.

Resistance to sunk costs. Resistance to sunk costs measures how well a participant ignores prior losses of time, money or other resources when deciding to continue investing in the sunk cost option. Responses are on a 6-point scale, where a '1' response means the participant prefers the sunk-cost option whereas the '6' response means the participant prefers the normatively correct option, which reflects the ability to ignore past loses and focus only on present consequences.

2.4. Crystallized intelligence

The vocabulary subscale of the Shipley-2 battery provided a well-validated indicator of crystallized intelligence (Kaya et al., 2012). The participant's task is to choose the word with the closest meaning to the presented target word. This test is comprised of 40 items and the scale was administered with a time limit of 10 min. The total number of correct answers is the final measure for this test.

2.5. Fluid intelligence

The Figure Series task represents a canonical measure of fluid intelligence. The participant is presented a sequence of figures and their task is to detect a rule governing each series and to choose the correct item that completes the series (Cattell and Horn, 1978). This task is comprised of 30 items in total with a time limit of 60 s per item. Performance is measured based on the total number of items answered correctly within 30 min.

2.6. Logical reasoning

To investigate logical reasoning skills, the logical reasoning subscale of Law School Admission Test (LSAT) was administered. The participant is presented a short verbal passage and is asked to answer a question about it. Questions are designed to evaluate a broad range of abilities involved in critical thinking, such as evaluating the assumptions and weight of the evidence underlying an argument. Five answer options are presented for each question and the participant's task is to use reasoning skills to select the best answer. Performance is measured according to the total number of items answered correctly within a 35 min time limit. The test is comprised of 25 items in total. Performance on the LSAT plays a central role in admittance to law school and represents a well-established measure of logical reasoning (Jackson, 1998).

2.7. MRI acquisition

The structural MRI protocol of the present study was implemented using a Siemens Magnetom Trio 3T whole-body MRI. All high-resolution T1-weighted brain images were acquired using a 3D Magnetization Prepared Rapid Gradient Echo Imaging (MPRAGE) protocol with 192 contiguous axial slices, acquired in sagittal orientation, echo time (TE) = 2.32 ms, repetition time (TR) = 1900 ms, field of view (FOV) = 230 mm, acquisition matrix 256 mm × 256 mm, slice thickness = 0.90 mm, and flip angle = 9°.

2.8. Surface-based morphometry

The CIVET analysis pipeline was applied to estimate several structural MRI features: Cortical Thickness (CTh), Cortical Surface Area (CSA) and Cortical Gray Matter Volume (CGMV) (Version 2.0; (Ad-Dab'bagh Y., 2006). The following analysis steps were performed to derive these indices: (1) linear registration (12-parameters) was employed to register the original T1-MRI image to ICBM 125 template; (2) radio-frequency and non-uniformities correction were applied to correct these images; (3) a brain mask was computed and the T1-MRI image was divided into masks differing by tissue type: white matter (WM), gray matter (GM), and cerebrospinal fluid (CSF); (4) high-resolution hemispheric surfaces were generated (163,842 vertices) and registered to a high-resolution template; (5) The different structural MRI features were computed for each vertex. CSA and CGMV were estimated by measuring the local variations of area/volume contraction and expansion relative to the vertex distribution on the surface template, while CTh was computed as the distance (mm) between the original WM and GM surfaces transformed back to the native space of the original MR images and interpolated onto the surface template then; (6) Finally, following CIVET guidelines, all outcomes were smoothed applying a 30-mm kernel (Chung et al., 2003) for CTh and 40-mm kernel for CSA and CGMV (Chung et al., 2001).

2.9. Statistical analysis

The following statistical analyses were performed to assess the cognitive and neural architecture of decision making competence.

2.10. Structural equation models

Structural Equation Modeling (SEM) was employed to explore the associations between decision making competence, crystallized intelligence, fluid intelligence, and logical reasoning. A confirmatory factor analysis (CFA) was performed to obtain a decision making competence latent factor based on the six subtests of the A-DMC. This latent factor captured the shared variance in performance across all measures of the A-DMC. Next, an SEM model was computed to study the association between the decision making competence latent factor and the other cognitive measures: Crystallized intelligence (Shipley Vocabulary), fluid intelligence (Figure Series) and logical reasoning (LSAT). The analyses were computed in Mplus 7 (Hallquist and Wiley, 2018) using maximum likelihood as the method of estimation. Model fit was evaluated using the root mean square error of approximation (RMSEA), and the comparative fit index (CFI). Values below 0.06 for RMSEA and close to 0.95 represent good fit (Hu and Bentler, 1999).

2.11. Associations between structural MRI features and cognitive measures

The relationship between structural MRI features (cortical thickness, cortical surface area, and cortical gray matter volume) and cognitive measures (decision making competence, crystallized intelligence, fluid intelligence, and logical reasoning) was explored at the vertex level. All surface-based morphometry models were computed with SurfStat created for MATLAB 7 (MathWorks, Inc.). SurfStat is a statistical toolbox created by Dr. Keith Worsley at the MNI (http://www.math.mcgill.ca/keith/surfstat/). These models were computed for each cognitive measure separately and for each structural MRI features. In these models, age and sex were included as covariates. Results were corrected for multiple comparisons by applying Random Field Theory (RFT) with a threshold of 5% ($p < 0.05$). The degree of spatial similarity between the outcomes for all cognitive measures was quantified using the Dice Coefficient (DC (Barbey et al., 2014; Bennett and Miller, 2010; Roman et al., 2014; Rombouts et al., 1997); for each structural MRI feature. DC is the ratio of the intersection of two sets to the union of the sets, and it has a range from 0 (no similarity) to 1 (perfect similarity). To compute DC, threshold maps were binarized (i.e. where the value '1' indicates a voxel with a significant p-value after RFT correction) and masked to include only those voxels inside the standardized brain volume. The formula $s=(2|V1\cap V2|)/(|V1|+|V2|)$ was employed to compute the similarity between maps, where Vi is the binary map corresponding to the different cognitive measure (e.g., 1 = adult decision making competence, 2 = fluid intelligence). Therefore, DC represents the number of overlapping (or shared) superthreshold voxels, divided by the average total superthreshold voxels of the images.

2.12. Investigating the unique variance in structural MRI measures explained by decision making competence

To investigate the unique associations between decision making competence and structural MRI features, we computed a model controlling for intelligence measures (crystallized and fluid intelligence), age, and sex. This model was also computed for logical reasoning (LSAT). In each case, RFT ($p < 0.05$) was applied to correct for multiple comparisons. In addition to these analyses, the unique associations of intelligence measures (crystallized and fluid intelligence) after controlling for decision making were examined. Finally, we examined the specific cognitive operations underlying the observed A-DMC sensitive regions with respect to the six subtests of the A-DMC, providing SEM evidence to further elucidate the neural architecture of specific facets of decision making competence.

3. Results

3.1. Structural equation modeling

The descriptive statistics and correlations between the administered tests were computed to examine the relationship between each of the cognitive variables. Table 1 presents the mean, median, and standard deviation for each subtest of the A-DMC, and for tests of crystalized intelligence, fluid intelligence, and logical reasoning. Overall, scores on each subtest of the A-DMC were higher in this sample than in the sample studied for the validation of the A-DMC (Bruine de Bruin et al., 2007). An effect size measure (Cohen *d*) was computed to estimate the magnitude of the differences between samples. The group difference was high for resistance to framing ($d = 0.87$), recognizing social norms ($d = 0.58$), and applying decision rules ($d = 1.86$).

Table 2 depicts the Pearson correlations between the components of the decision making competence battery and each of the administered cognitive tests. The A-DMC subtests were moderately correlated with one other (range:0.05–0.35). All correlations were positive, although the "over/under-confidence" subtest was not reliably associated with the other subtests. The highest correlation was found between "applying decision rules" and "consistency in risk perception" ($r = 0.343, p < .001$). Overall, the profile of correlations observed here is similar to that reported by Bruine de Bruin and colleagues (range: -.01–0.43 (Bruine de Bruin et al., 2007);). Fisher's z transformation was employed to determine if the magnitude of each correlation was different between samples. Non-significant results were found for most of the comparisons (*ps* > .05; range: 0.064 - 0.968), with the exception of the correlation between "under/over confidence" and "applying decision rules", where a higher correlation was found for the original sample ($r = .31$ vs. $r = .06$, $Z = 3.29$, $p = .002$). Among the administered tests of intelligence, the logical reasoning test demonstrated the highest correlation with the A-DMC subtests (range: 0.12–0.48), followed by crystallized intelligence (ranging from 0.05 to 0.40), and fluid intelligence (ranging from 0.03 to 0.37). The A-DMC subtest, "applying decision rules", demonstrated the strongest association with tests of intelligence ($r = 0.403$, $p < .001$ and $r = 0.366$, $p < .001$ for fluid and crystallized intelligence respectively) and logical reasoning ($r = 0.470$, $p < .001$). Fisher's z transformation for repeated measures (Meng et al., 1992) was computed to determine if the magnitude of the correlation between fluid and crystallized intelligence and logical reasoning with the A-DMC subtest measures administered was of the same magnitude. A Fisher's z transformation value higher than |1.96| reveals a statistically significant difference ($p < .05$). Specifically, logical reasoning showed a higher correlation than fluid intelligence with "consistency in risk perception" (0.351 vs. 0.223, $Z = 2.10$) and "resistance to framing" (0.389 vs. 0.292, $Z = 2.33$). Moreover, logical reasoning obtained higher correlations than crystallized intelligence in several A-DMC subtests: "consistency in risk perception" (0.351 vs. 0.216, $Z = 2.26$), "resistance to sunk cost" (0.185 vs. 0.035, $Z = 2.53$) and "applying decision rules" (0.470 vs. 0.366, $Z = 1.97$).

Second, we investigated whether the decision making competence index (Bruine de Bruin et al., 2007) can be estimated through Confirmatory Factor Analysis (CFA). Appendix 1 presents the one-factor structure for the A-DMC battery, including the factor weight of each component. The fit of the model was excellent (RMSEA < 0.001; CFI = 1.000). At a descriptive level, these results were similar to the results of the exploratory factor analysis reported by Bruine de Bruin and colleagues (Bruine de Bruin et al., 2007). The only exception was the "over/under confidence" component, which exhibited a factor loading lower than expected.

Third, we computed an SEM model to investigate the associations between the decision making competence latent factor and each subtests of the A-DMC and test of intelligence and reasoning. The results of this model are illustrated in Fig. 1. The fit indices of the model were excellent (RMSEA = 0.022 and CFI = 0.991). All intelligence measures demonstrated positive factor loadings. The highest association between tests of intelligence and reasoning was found for measures of logical reasoning and crystallized intelligence test ($r = 0.50, p < .001$), followed by logical reasoning and fluid intelligence ($r = 0.35, p < .001$). The measures of crystallized and fluid intelligence were also positively correlated, but the magnitude of the correlation was lower ($r = 0.16, p = .006$). Associations

Table 1
Mean (*M*) and Standard Deviation (*SD*) of the components of the decision-making competence battery (A-DMC), crystallized intelligence (*Gc*), fluid intelligence (*Gf*) and logical reasoning. LSAT = Law School Admission Test.

	Potential range	INSIGHT sample (*N* = 283)			Original sample (*N* = 360)			Differences samples
		Observed range	*M*	*SD*	Observed range	*M*	*SD*	*d*
A-DMC Components								
Resistance to Framing	.00/5.00	2.50/5.00	4.18	0.43	1.00/4.92	3.72	0.61	**0.87**
Recognizing Social Norms	−1.00/1.00	−0.41/0.88	0.47	0.22	−0.59/0.84	0.33	0.26	**0.58**
Under/Over confidence	.00/1.00	0.69/1.00	0.92	0.06	0.50/1.00	0.91	0.08	0.14
Applying Decision Rules	.00/1.00	0.33/1.00	0.82	0.16	0.00/1.00	0.44	0.24	**1.86**
Consistency in Risk Perception	.00/1.00	0.40/1.00	0.74	0.11	0.20/1.00	0.70	0.16	0.29
Resistance to Sum Costs	1.00/6.00	2.00/6.00	4.31	0.71	1.00/6.00	4.40	0.77	−0.12
Intelligence Battery								
Figure Series	0.00/30.00	3.00/30.00	18.90	4.81	–	–	–	–
LSAT	0.00/25.00	1.00/25.00	12.63	4.07	–	–	–	–
Vocabulary	0.00/40.00	20.00/40.00	32.16	3.61	–	–	–	–

Note. All subtests of the decision-making competence battery are scored so that higher numbers reflect better performance.

Table 2
Pearson correlations (and *p* values) between components of decision-making battery and crystallized intelligence (*Gc*), fluid intelligence (*Gf*) and logical reasoning. LSAT = Law School Admission Test.

	2.	3.	4.	5.	6.	7.	8.	9.
1. Under/Over confidence	.051 (.393)	.055 (.355)	-.077 (.197)	.058 (.328)	.086 (.147)	.124* (.037)	.046 (.437)	.121* (.042)
2. Consistency in Risk Perception	1	.175** (.003)	.197* (.001)	.343*** (<.001)	.292*** (<.001)	.223*** (<.001)	.216*** (<.001)	.351*** (<.001)
3. Recognizing Social Norms		1	.139* (.019)	.207*** (<.001)	.188** (.002)	.249*** (<.001)	.131* (.027)	.190** (.001)
4. Resistance to Sunk Costs			1	.197*** (.001)	.104 (.081)	.035 (.563)	.215*** (<.001)	.185** (.002)
5. Applying Decision Rules				1	.291*** (<.001)	.366*** (<.001)	.403*** (<.001)	.470*** (<.001)
6. Resistance to Framing					1	.292*** (<.001)	.241*** (<.001)	.389** (<.001)
7. *Gc* (Vocabulary)						1	.165** (.005)	.501*** (<.001)
8. *Gf* (Figure Series)							1	.350*** (<.001)
9. Logical reasoning (LSAT)								1

*p < .05; **p < .01; ***p < .001.

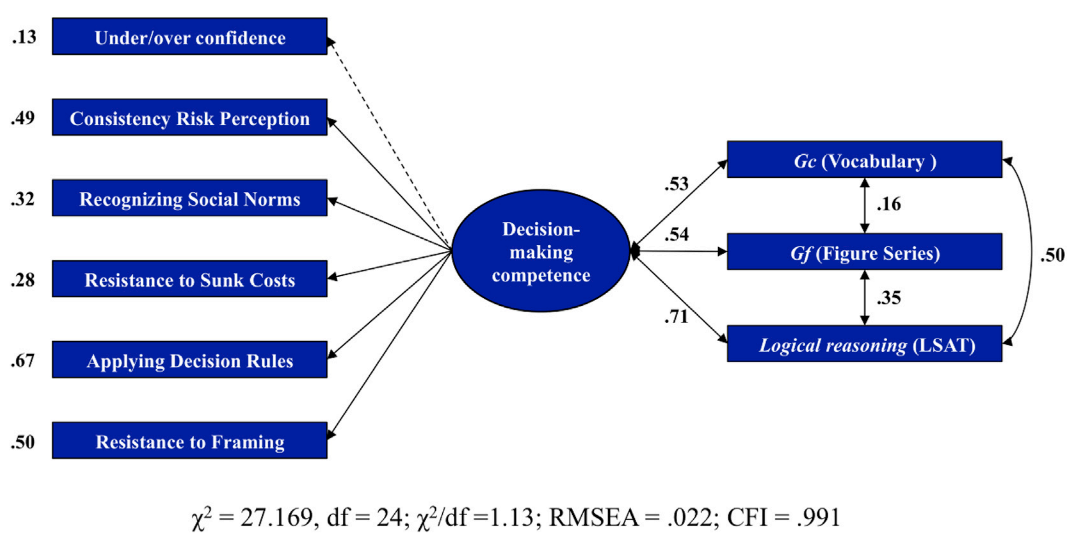

Fig. 1. Structural equation model of adult decision-making competence, intelligence measures, and logical reasoning. Broken lines depict non-significant weights. *Gc* = crystallized intelligence; *Gf* = fluid intelligence; LSAT = Law School Admission Test.

between the latent decision making score and the other cognitive measures demonstrated that all correlation values were positive and of medium or large magnitude. The highest correlation was observed between decision making competence and logical reasoning ($r = 0.71$, $p < .001$), while the associations with measures of crystallized and fluid intelligence were moderate ($r = 0.40$ and $r = 0.53$ respectively) ($ps < .001$).

3.2. Associations between structural MRI features and cognitive measures

We applied SEM to investigate the association between cortical thickness, cortical surface area, and cortical gray matter volume and the administered tests of decision making competence (A-DMC), crystallized intelligence (Shipley Vocabulary), fluid intelligence (Figure Series), and logical reasoning (LSAT). Age and sex were included as covariates in each model. In addition, the Dice Coefficient (DC) was computed to investigate the spatial similarity between the administered cognitive measures for each of the structural MRI features.

3.3. Cortical thickness

We examined the statistically significant associations between cortical thickness and each cognitive measure (see Appendix 2). All results were corrected for multiple comparisons using random field theory (RFT). For the decision making measure, two clusters were found as significant at bilateral middle temporal lobe (p corrected-left = 0.031; p corrected-right = 0.012). Regarding fluid intelligence, several areas were found as significant: right posterior cingulate cortex (p corrected = 0.018) and left posterior cingulate cortex (p corrected = 0.031), right posterior superior temporal sulcus (p corrected = 0.005), right temporal pole (p corrected = 0.003), and left inferior temporal (p corrected < 0.001). The significant results for crystallized intelligence were located within the left superior temporal lobe (p corrected = 0.042). Finally, significant results for logical reasoning were observed within the bilateral middle temporal lobe (p corrected-left = 0.029; p corrected–right = 0.041) and the right inferior temporal lobe (p corrected = 0.007).

In addition, spatial similarity among the observed cortical thickness findings (see Appendix 2) for measures of decision making competence, crystallized intelligence, fluid intelligence, and logical reasoning were examined using the Dice Coefficient. The spatial similarity (DC) between decision making competence and the intelligence measures was small for fluid intelligence (DC = 0.26), null for crystallized intelligence, and of moderate for logical reasoning (DC = 0.49). Note that the highest correlation in the SEM model was also found between decision making competence and logical reasoning ($r = 0.71$, $p < .001$). In addition, the DC between fluid intelligence and logical reasoning was of medium size (DC = 0.15). However, at the behavioral level, logical reasoning was more strongly related to crystallized intelligence than fluid intelligence ($r = 0.50$ and $r = 0.35$ respectively) ($ps < .001$).

3.4. Cortical surface area

The results for cortical surface area were weaker than for the cortical thickness measures (see Appendix 3). Specifically, the results for decision making competence were found in left dACC (p corrected = 0.044) and left fusiform area (p corrected = 0.046). The associations between cortical surface area and logical reasoning were observed within left dACC (p corrected = 0.022). Spatial overlap was observed only between decision making competence and logical reasoning (DC = 0.55), given that no significant associations were found after RFT correction for crystallized and fluid intelligence.

3.5. Cortical gray matter volume

With respect to cortical gray matter volume (see Fig. 2), decision making competence engaged a broadly distributed network of regions, including left orbitofrontal cortex (p corrected = 0.014), left fusiform (p corrected = 0.014), right posterior superior temporal sulcus (STS) (p corrected = 0.008), and right occipital lobe (p corrected = 0.025). No significant associations were found for crystallized intelligence, while the associations for fluid intelligence were observed within the left fusiform (p corrected = 0.045) and right occipital cortex (p corrected = 0.048). Finally, the results for logical reasoning were located within left dACC (p corrected = 0.015), right posterior superior temporal sulcus (p corrected = 0.010), and right parahippocampal gyrus (p corrected = 0.047).

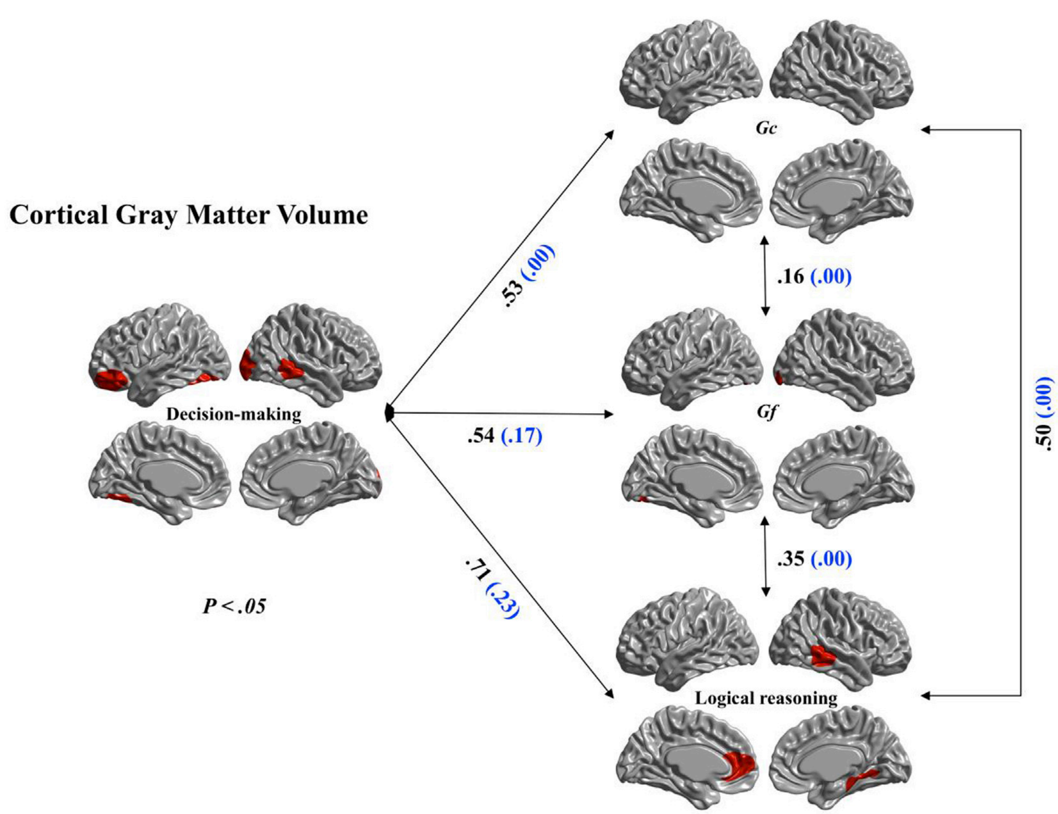

Fig. 2. Cortical gray matter volume results for decision-making competence, crystallized intelligence (*Gc*), fluid intelligence (*Gf*), and logical reasoning. Correlation values among measures are illustrated in black. Dice coefficients of the spatial similarity among brain regions for each measure are illustrated in blue. In each map the left hemisphere is on the reader's left. Maps are corrected for multiple comparisons ($p < .05$).

Again, the highest overlap was found between decision making competence and logical reasoning (DC = 0.23), while a small association was observed for decision making competence and fluid intelligence (DC = 0.17). The spatial similarity between fluid intelligence and logical reasoning was null.

3.6. Investigating the unique variance in structural MRI measures explained by decision making competence

To further isolate the neural substrates of decision making competence, we repeated the analyses including logical reasoning, fluid intelligence, and crystallized intelligence as covariates in the model. Null results were found when all other cognitive factors were included as covariates. However, results for decision making competence and logical reasoning were found in similar areas with a substantial degree of overlap (DC range: 0.23–0.55). Therefore, we repeated the analyses separately for decision making competence and logical reasoning. For both measures, we controlled for performance on tests of intelligence (fluid intelligence and crystallized intelligence). Results for cortical surface area and cortical gray matter volume are shown in Fig. 3 ($p < 0.05$, corrected for multiple comparisons). Cortical surface area within left dACC (p corrected = 0.048) and right STS (p corrected = 0.047) and cortical gray matter volume within right STS (p corrected = 0.044) accounted for individual differences in decision making competence. Furthermore, variability in cortical surface area within left dACC (p corrected = 0.048) was associated with individual differences in logical reasoning, but the outcomes were null for cortical gray matter volume. With respect to cortical thickness, the results for decision making competence and logical reasoning were null. The degree of overlap between the results found for decision making and logical reasoning was of medium size for cortical surface (DC = 0.28) and null for cortical gray matter volume (DC = 0.00).

In addition, we explored the unique associations of crystallized and fluid intelligence after controlling for individual differences in decision making competence (see Appendix 4). The unique associations of fluid intelligence were located in the right precuneus (p corrected = 0.007) for the cortical thickness index, while no significant results were found for crystallized intelligence.

The final step in our analysis was to further probe the relationship between the unique cortical surface area regions of decision making competence with each component of the A-DMC battery for cortical surface area and for cortical gray matter volume regions (Fig. 4). Since the anatomical regions were selected based on the correlation previously found for decision making competence, the results can be seen as descriptive. The left dACC was associated with “applying decision rules” ($r = 0.120$, $p = .043$), and “resistance to framing” ($r = 0.208$, $p < .001$) while the right posterior superior temporal sulcus (STS) was associated with “consistency risk perception” ($r = 0.208$, $p < .001$), “recognizing social norms” ($r = 0.127$, $p = .031$), “applying decision rules” ($r = 0.143$, $p = .015$) and “resistance to framing” ($r = 0.138$, $p = .020$).

4. Discussion

Although cognitive neuroscience has made remarkable progress in understanding the neural foundations of goal-directed behavior and decision making, neuroscience research on *decision making competence*, the capacity to resist biases in human judgment and decision making, remains to be established. Here, we investigated the cognitive and neural mechanisms of decision making competence in 283 healthy young adults. We administered the Adult Decision Making Competence battery to assess the respondent's capacity to resist standard biases in decision making, including: (1) resistance to framing, (2) recognizing social norms, (3) over/under confidence, (4) applying decision rules, (5) consistency in risk perception, and (6) resistance to sunk costs. In addition, the present study characterized the relationship between decision making competence and multiple measures of intelligence, applying structural equation modeling (SEM) to assess associations with performance on tests of crystallized intelligence (Shipley Vocabulary), fluid intelligence (Figure Series), and logical reasoning (LSAT). To further isolate the neural mechanisms of decision making competence, we examined the unique contributions of cortical regions to decision making competence while controlling for performance on intelligence test (fluid and

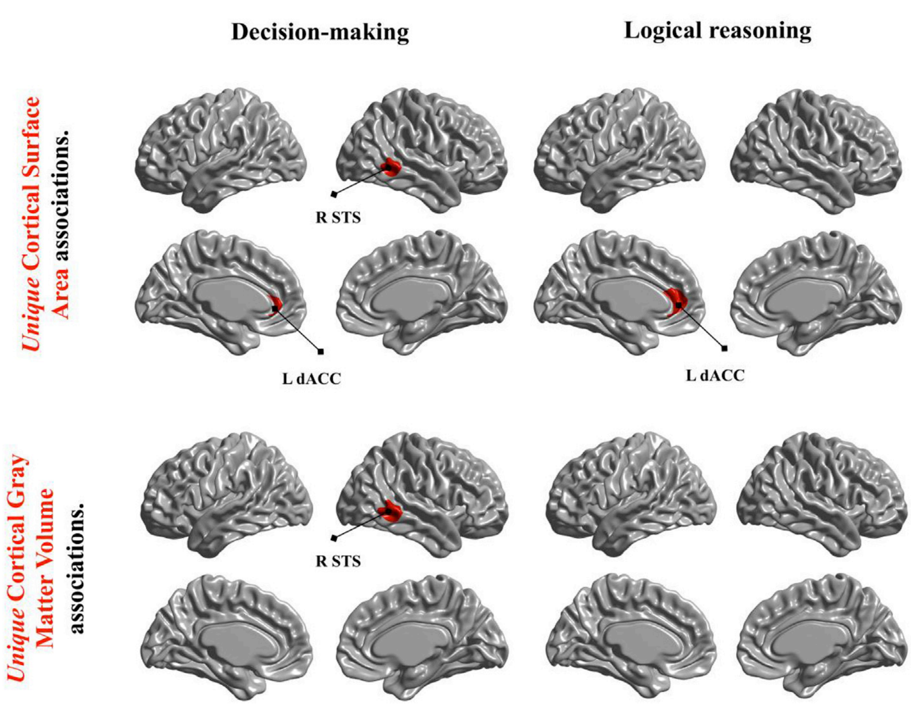

Fig. 3. Brain regions whose cortical gray matter volume is uniquely associated with decision-making competence, and logical reasoning after controlling for individual differences in fluid intelligence, age and sex. Maps are corrected for multiple comparisons ($p < .05$). DC = Dice coefficient. L = left and R = right. dACC = dorsal anterior cingulate cortex, STS = right posterior superior temporal sulcus.

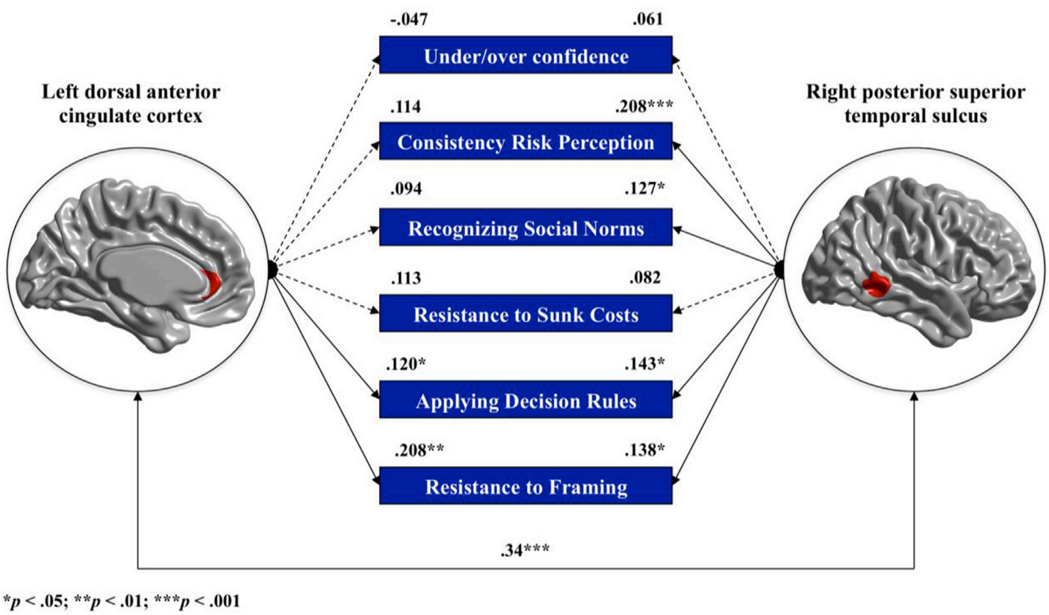

Fig. 4. Correlations between unique cortical surface area regions with each subtest of decision-making competence. Broken lines depict non-significant correlations.

crystallized measures). Finally, we examined the specific cognitive operations underlying the observed A-DMC sensitive regions with respect to the six subtests of the A-DMC, providing SEM evidence to further elucidate the neural architecture of specific facets of decision making competence. Our findings support the following primary conclusions.

4.1. Investigating the relationship between decision making competence and facets of intelligence

The reported SEM analysis demonstrated a strong relationship between decision making competence and performance on tests of logical reasoning (LSAT); $r = 0.71$; Fig. 1). This finding provides evidence that decision making competence engages cognitive operations for critical thought and deliberation – for example, when evaluating the assumptions and weight of the evidence underlying an argument. Thus, the capacity to overcome decision biases and to demonstrate competence in decision making is associated with performance on standardized tests of logical reasoning (i.e., LSAT).

Reliable associations were also observed between decision making competence and measures of crystallized and fluid intelligence ($r = 0.53$ and 0.54, respectively; Fig. 1). The observed pattern of correlations provides evidence that the capacity to resist biases in decision making depends on cognitive processes for both crystallized and fluid intelligence. Indeed, research indicates that prior knowledge and experience (crystallized intelligence), along with the capacity for adaptive reasoning and problem solving (fluid intelligence), support the generation and evaluation of hypotheses in decision making (for a review see (Gilovich et al., 2002)) and therefore corroborate the results of the present study.

Further examination of specific A-DMC subtests revealed correlations of low to moderate value (ranging from 0.03 to 0.29), with the exception of the "applying decision rules" subtest, which exhibited higher correlations (logical reasoning: $r = 0.47$; crystallized intelligence: 0.37; fluid intelligence: 0.40). This pattern of findings reflects a common reliance on mechanisms for the detection and use of decision rules for goal-directed, intelligent behavior (Bennett et al., 1990; Payne et al., 1993; Raven et al., 1998). Our findings support the idea that decision making, reasoning, and intelligence are related cognitive abilities, but the small effect sizes indicate that these domains also rely upon distinct mechanisms. Thus, decision making competence demonstrates variability that cannot be fully explained by performance on tests of intelligence and reasoning – variability that can be further explored by investigating the neural mechanisms underlying each cognitive domain (Bruine de Bruin et al., 2007).

The strong positive correlation among performance on tests of decision making competence and logical reasoning was accompanied by a high degree of spatial similarity, reflecting individual differences in cortical surface area primarily within left dACC (DC = 0.28). Prior neuroscience research demonstrates that the dACC plays a central role in adaptive behavior and decision making, providing evidence that this region is critical for cognitive control and the optimization of choice behavior (for a review, see (Heilbronner and Hayden, 2016)). The findings of the present study further establish the role of the dACC in decision making competence, demonstrating that individual differences in the cortical surface area of this region is associated with cognitive control and the capacity to overcome biases in human judgment and decision making.

The association between these structural indices and intelligence measures were weaker than the results found for decision-making. The associations between structural brain indices and Gc were null, with the exception of cortical thickness where the outcomes were located in the superior temporal pole. Similarly, Colom et al. (2009) found a non-overlapping cluster of Gc in the superior temporal pole after removing the effects of general and visuospatial intelligence. Regarding fluid intelligence, the associations between cortical thickness and Gf were distributed across several brain areas, as in previous studies (Karama et al., 2011; Joshi et al., 2011). However, the associations between Gf and cortical surface area were null. The number of studies addressing the relationship between intelligence and cortical surface area are smaller than for cortical thickness (e.g., Fleischman et al., 2014; Román et al., 2014). Some studies found stronger associations between surface area and intelligence than between the latter and thickness (e.g., Vuoksimaa et al., 2015).

4.2. Unique Characteristics of decision making competence and facets of intelligence

Accumulating evidence indicates that decision making competence reflects individual differences in critical thought and self-reflection, skills that enable the respondent to identify and resist biases in decision making (Evans and Stanovich, 2013). These skills are not directly assessed by neuropsychological tests of intelligence, which are instead designed to examine core cognitive abilities, such as working memory capacity (Colom et al., 2013). This distinction motivates contemporary theories of intelligence, which propose two primary systems of thought – one that captures individual differences in *rational thinking dispositions* (e.g., critical thinking skills) and another that reflects individual differences in *core cognitive abilities* (e.g., performance on tests of working memory (Evans and Stanovich, 2013). The present study further supports this distinction, providing evidence that critical thinking skills, as assessed by decision making competence, and measures of intelligence depend on separable but related cognitive processes. Indeed, reliable correlations between decision making competence and crystallized and fluid intelligence were observed ($r = 0.53$ and 0.54, respectively; Fig. 1), but with significant variance in decision making that remained to be explained.

We further examined the unique structural brain imaging correlates of decision making competence when controlling for performance on related tests of fluid intelligence. The results revealed individual differences in cortical surface area within left dACC. Thus, the associations between decision making competence and cortical gray matter volume previously observed within orbitofrontal, occipital, and fusiform regions disappeared after controlling for intelligence measures (fluid and crystallized intelligence). These results support the idea of cortical surface area as a structural MRI index stronger associated with higher-order cognition process (e.g., intelligence) than cortical thickness (Colom et al., 2013; Fleischman et al., 2014; Román et al., 2014; Vuoksimaa et al., 2015). Cortical gray matter volume combines cortical thickness and cortical surface area, and, therefore, the results found for volume are not independent.

This pattern of findings further supports the behavioral results indicating that decision making competence and fluid intelligence depend on separable but related processes, demonstrating both shared (e.g., orbitofrontal cortex) and distinct (e.g., dACC) cortical regions in each domain. The unique reliance upon dACC for decision making competence further suggests that mechanisms for critical thought and logical reasoning are not reliably engaged by neuropsychological tests of fluid intelligence, supporting the contemporary view that intelligence tests are instead designed to measure core facets of cognitive ability (e.g., working memory capacity) (Evans and Stanovich, 2013).

We also investigated the contribution of these regions in each A-DMC subtest, examining the structural brain imaging correlates of specific facets of decision making competence. Individual differences in cortical surface area within left dACC was associated with performance on multiple A-DMC subtests, including "applying decision rules", "resistance to sunk cost", and "resistance to framing." These tasks are known to recruit mechanisms for cognitive control, engaging critical thinking skills that enable the respondent to apply decision rules to reason logically about the problem and to resist biases due to the framing of the problem or a tendency to focus on prior investments despite future losses (for a review see (Gilovich et al., 2002)).

An analysis of individual differences in cortical gray matter volume revealed reliable effects within right posterior STS for multiple A-DMC subtests, including "consistency in risk perception", "recognizing social norms", "resistance to sunk costs", "applying decision rules", and "resistance to framing". The right posterior STS is known to play a central role in processing the intentions underlying actions, the context in which actions occur, and is particularly sensitive to the outcome of goal-directed actions (Shultz et al., 2011). Thus, the engagement of this region in multiple facets of decision making competence reflects the importance of processes for representing intentions (e.g., "recognizing social norms"), contexts (e.g., "consistency in risk perception"), and outcomes in decision making (e.g., "applying decision rules").

4.3. *Decision making competence and logical reasoning*

The reported SEM analysis demonstrated that decision making competence was highly correlated with performance on tests of logical reasoning ($r = 0.71$), supporting the role of critical thought and reasoning skills in decision making. Furthermore, the highest associations were found for the "applying decision rules" ($r = 0.47$), "resistance to framing" ($r = 0.39$) and "consistency in risk perception" subtests ($r = 0.35$), all of which represent core facets of decision making competence that rely upon skills for logical reasoning.

A similar pattern of results was observed for structural neuroimaging measures of decision making competence and logical reasoning. A significant degree of spatial similarity was observed for decision making competence and logical reasoning across multiple structural brain imaging measures (DC = 0.49, 0.55 and 0.23 for cortical thickness, cortical surface area, and cortical gray matter volume, respectively). Moreover, we investigated the unique variance in logical reasoning after removing the variance explained by fluid intelligence, using the same approach applied to study the unique variance accounted for by decision making competence. In each case, a similar pattern of findings was observed, engaging regions primarily within left dACC. The degree of spatial similarity was 28% for cortical surface area. Therefore, the observed pattern of associations indicate that decision making competence and logical reasoning engage similar cognitive and neural mechanisms. Indeed, the logical reasoning measure of the LSAT is designed to examine critical thought and reasoning (e.g., evaluating the assumptions and weight of the evidence underlying an argument), skills that also play a central role in resisting biases and exhibiting competence in decision making.

5. Conclusions

The present study provides novel evidence that: (i) decision making competence is associated with cognitive operations for logical reasoning, and that (ii) these convergent processes are associated with individual differences in cortical surface area primarily within left dACC and cortical gray matter volume within right posterior STS. Our findings motivate an integrative framework for understanding the neural mechanisms of decision making competence, suggesting that individual differences in the cortical surface area within left dACC and right STS are associated with the capacity to overcome decision biases and exhibit competence in decision making.

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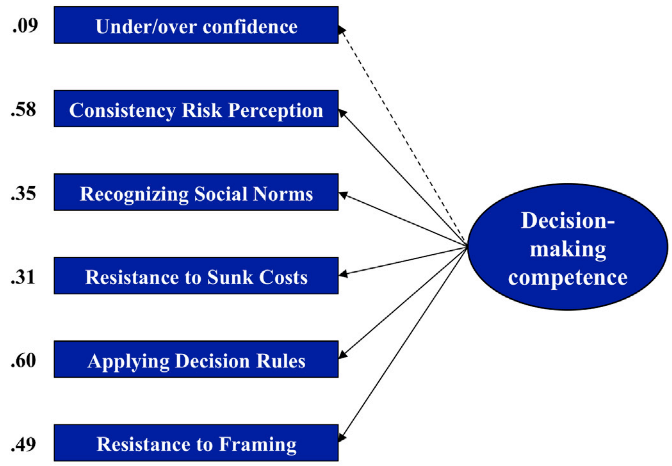
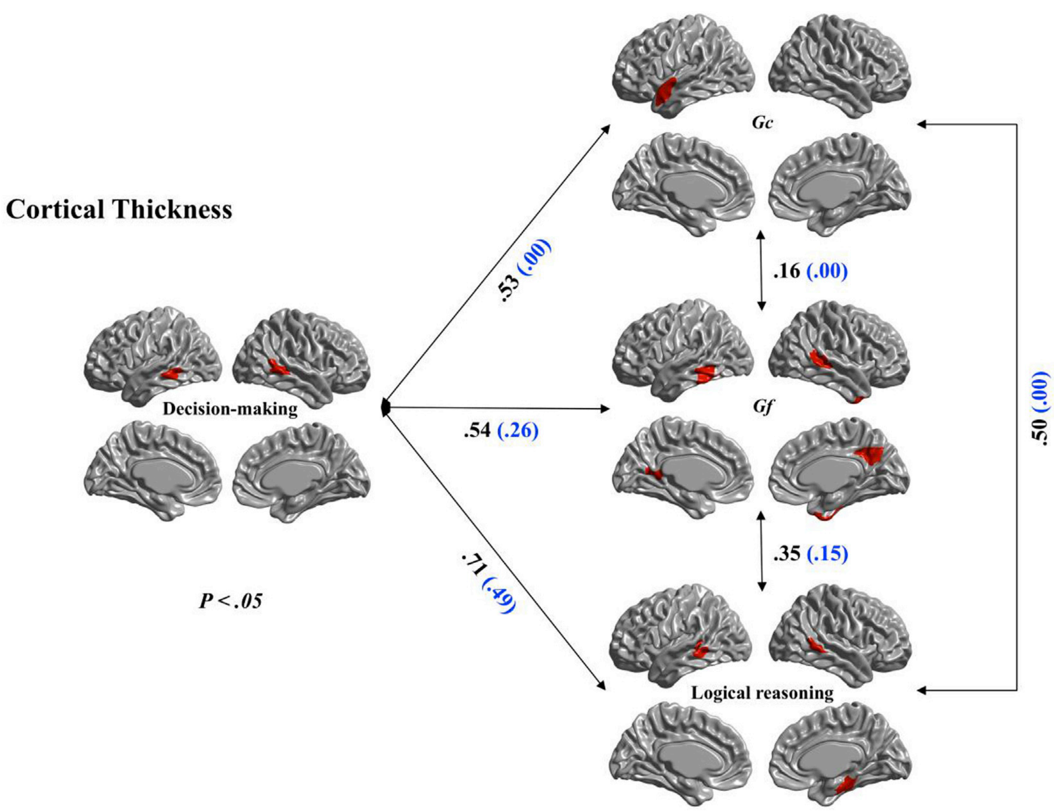
Appendix 1. Confirmatory factor analysis of the decision-making competence. Broken lines depict non-significant weights.

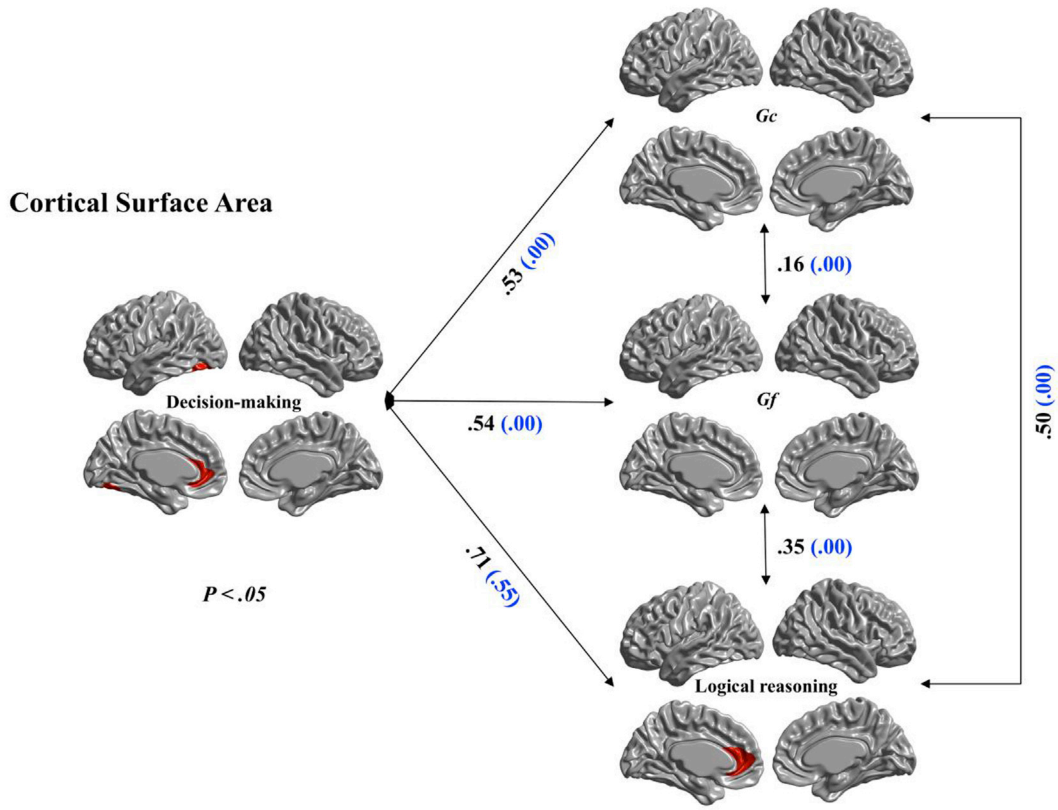


χ^2 = 5.639, df = 9; χ^2/df =.63; RMSEA = .000; CFI = 1.000

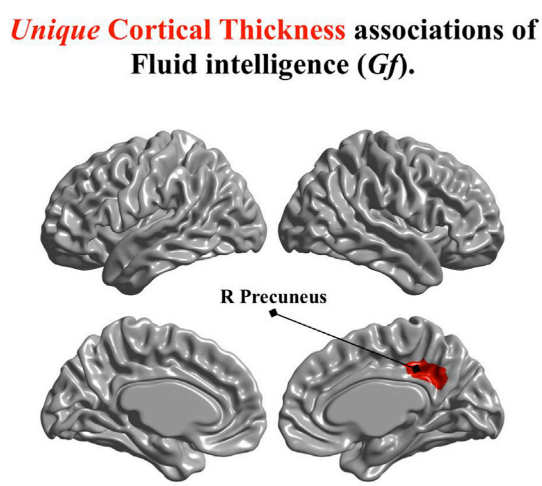
Appendix 2. **Cortical thickness results for decision-making competence, crystallized intelligence (*Gc*), fluid intelligence (*Gf*), and logical reasoning. Correlation values among measures are illustrated in black. Dice coefficients of the spatial similarity among brain regions for each measure are illustrated in blue. In each map the left hemisphere is on the reader's left.**



Appendix 3. **Cortical surface area results for decision-making competence, crystallized intelligence (*Gc*), fluid intelligence (*Gf*), and logical reasoning. Correlation values among measures are illustrated in black. Dice coefficients of the spatial similarity among brain regions for each measure are illustrated in blue. In each map the left hemisphere is on the reader's left.**



Appendix 4. Brain regions whose cortical thickness is uniquely associated with fluid intelligence after controlling for individual differences in decision-making, age and sex. Maps are corrected for multiple comparisons ($p < .05$). R = right.



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