Gaze data reveal individual differences in relational representation processes

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Abstract

In our everyday life, we often need to anticipate the potential occurrence of events and their consequences. In this context, the way we represent contingencies can determine our ability to adapt to the environment. However, it is not clear how agents encode and organize available knowledge about the future to react to possible states of the world. In the present study, we investigated the process of contingency representation with three eye-tracking experiments. In Experiment 1, we introduced a novel Relational-inference task in which participants had to learn and represent conditional rules regulating the occurrence of interdependent future events. A cluster analysis on early gaze data revealed the existence of two distinct types of encoders. A group of (sophisticated) participants built exhaustive contingency models that explicitly linked states with each of their potential consequences. Another group of (unsophisticated) participants simply learned binary conditional rules without exploring the underlying relational complexity. Analyses of individual cognitive measures revealed that cognitive reflection is associated with the emergence of either sophisticated or unsophisticated representation behavior. In Experiment 2, we observed that unsophisticated participants switched towards the sophisticated strategy after having received information about its existence, suggesting that representation behavior was modulated by strategy generation mechanisms. In Experiment 3, we showed that the heterogeneity in representation strategy emerges also in conditional reasoning with verbal sequences, indicating the existence of a general disposition in building either sophisticated or unsophisticated models of contingencies.

Keywords: representation, eye-tracking, strategy generation, cognitive abilities, individual differences

Introduction

The main challenge we face in our everyday experience is adapting to the environment we live in. We need to foresee that some events might take place in the future, and to be aware of the possible consequences of their occurrence (Schultz et al., 1997; Suddendorf & Corballis, 2007). However, our world is not always predictable: we can learn how to respond to a specific event, but we may not know whether this event will actually occur. For example, I know that I will have to take the bus if the train does not arrive, but the (non-) arrival of the train is in some way unforeseeable. In this context, the way we encode and organize relevant knowledge about the world (i.e. the type of environmental representation we generate) can affect our ability to respond to future events (Bar, 2007; Gilbert & Wilson, 2007). On the one hand, agents may build an exhaustive representation of the relational structure underlying interrelated contingencies and plan future behavior taking into consideration every predictable consequence of potential states. In our example, I am prepared for the possibility that the train does not arrive, and so I bring my bus pass in order to be ready to respond optimally to the occurrence of both states of the world. On the other hand, agents may learn only basic units of knowledge (e.g. binary associations between a state and an outcome), without building an explicit model of how these simple rules relate to each other. Only once a specific condition takes place, these latter agents would use stored knowledge to react to that specific event. In our example, this representation process would lead me to realize that I need the bus pass only after apprehending that the train has not arrived, potentially catching me unprepared (i.e. I may have left the bus pass at home). These two types of representation process express different degrees of sophistication: despite the latter behavior might be occasionally efficient, the former is more sophisticated since it is suitable for responding optimally to every predictable environmental contingency. Although this behavioral difference is reminiscent of the distinctions between rule abstraction and memorization in category learning (McDaniel et al.,

2014), proactive and reactive cognitive control (Braver, 2012), model-based and model-free learning (Daw et al., 2005, 2011; Konovalov & Krajbich, 2016) and problem-model and direct-translation strategies in problem-solving (Boote et al., 2016; Mayer & Hegarty, 1996), it is still unclear how agents build internal contingency models starting from available relational knowledge. In particular, we should understand whether distinct processes of relational representation do exist, as well as the cognitive sources of this heterogeneity. In order to explore these issues, we ran three different eye-tracking experiments.

In Experiment 1, we designed a novel Relational-inference task in which each trial was composed of two phases: Representation and Response. In the Representation phase, participants had a limited amount of time to learn triplets of between-state rules connected by higher-order transitive relations (i.e. if the state X occurs, then the state Y follows; if the state Y occurs, then the state Z follows; if the state Z occurs, then the state W occurs as well). These pieces of information established the conditional relations regulating the occurrence of states, but did not provide information about their actual occurrence (i.e. participants know that state Y follows from the occurrence of state X, but do not know if state X will actually occur). In the Response phase, the occurrence of a specific state was disclosed, and participants had to infer which other states necessarily followed given the relational model acquired in the Representation phase. In the Relational-inference task, we used eye-tracking to explore top-down attentional mechanisms including search, selection and binding of relevant information, which can reveal how agents spontaneously build representations of the current relational environment. Specifically, in the Representation Phase, we expect some (sophisticated) participants to explore the environment searching for all possible relational information in order to construct a representation that explicitly expresses all the existing relations between states. Conversely, unsophisticated agents should not explore the relational properties of the

current relational set, since they do not aim to build a comprehensive model of the relational structure of the environment.

Results of a cluster analysis on early gaze data in the Representation phase confirmed the existence of two distinct groups of participants that respectively exhibited sophisticated and unsophisticated behaviors, and showed marked differences in task performance.

In order to explore the cognitive mechanisms driving heterogeneity in representation behavior, in Experiment 2 we collected data on a new pool of participants performing the Relational-inference task in two different sessions (pre- and post- treatment). In the pre-treatment session, participants performed the Relational-inference task with the same modalities of Experiment 1. At the beginning of the post-treatment session, the same participants were informed about the existence of sophisticated and unsophisticated strategies and their respective average efficiencies. Then they were asked to complete again the Relational-inference task in the way they preferred. We therefore compared the representation strategy implemented by participants in the two sessions. We found a notable strategy switch from the unsophisticated towards the sophisticated strategy, suggesting that the implementation of a specific strategy is not driven by cognitive capacity or motivation, but rather by strategy generation mechanisms.

In Experiment 3, we investigated whether the heterogeneity in Experiment 1 and 2 could generalize to a Verbal-Inference task requiring conditional reasoning in real life scenarios. The Verbal-inference task differed from the Relational-inference task in different ways. First, it included verbal instead of symbolic content, setting conditional reasoning in a more naturalistic context; second, task resolution was not dependent on short-term memory components and encoding time constraints. The Verbal-inference task was completed by participants of Experiment 2, since we aimed to compare individual representation strategies in the two tasks. Results show that sophisticated participants, as defined in the Relational-inference Task, spontaneously adopted sophisticated representation behavior in the Verbal-Inference task,

suggesting the existence of general, context-independent processes of encoding, integration and representation of relational information between hypothetical states of the world.

Cognitive drivers of sophisticated and unsophisticated representation processes

To date, we lack evidence about the contribution of cognitive abilities in modulating representation-building mechanisms. We can hypothesize that high working memory is necessary for the generation of sophisticated representations, since it constitutes the workspace where relational representations are constructed (Doumas et al., 2008; Halford et al., 2010), and guarantees that agents can build, retain and update representations (Oberauer et al., 2009). However, it is possible that working memory sustains active maintenance and manipulation of representations without affecting the type of representation that is generated. To investigate the role of working memory in these processes, we collected four different working memory measures: digit span forward and backward (Wechsler, 2008) and the n-back task (in two versions of increasing difficulty, 2-back and 3-back, Kirchner et al., 1958). The forward version of the digit span assesses simple short-term maintenance and recall of elements in working memory, while the backward version requires the additional component of mental manipulation of digits (Baddeley, 1996; Koenigs et al., 2009; Monaco et al., 2013). The n-back task tests the ability to maintain and update a dynamic set of information, targeting processes related to cognitive control, such as inhibition and interference resolution (Kane, Conway, Miura, & Colflesh, 2007).

Another cognitive ability that could intervene in the representation process is fluid intelligence, which expresses the ability to adapt to unknown contexts and reason on abstract information with minimal dependence on crystalized knowledge (Cattell, 1963). However, we do not know if fluid intelligence intervenes in an early stage of representation generation or simply sustain updating and inferential mechanisms, as recently suggested by Shipstead et al. (2016). To

collect individual measures of fluid intelligence, we tested participants on the Raven Advanced Progressive Matrices Test (APM; Raven et al., 1998).

Finally, we investigated whether cognitive reflection, measured by the Cognitive Reflection Test (CRT; Frederick, 2005), could be a potential candidate to predict the existence of distinct representation processes. The CRT traditionally assesses the individual tendency to implement either reflective or reflexive cognitive processes. In particular, a high cognitive reflection level expresses the ability to reason exhaustively about the characteristics of a problem, inhibiting intuitive but incorrect responses. Conversely, a low cognitive reflection level indicates an aptitude for generating heuristics on salient information at the expense of problem understanding (Toplak et al, 2011; 2014). In recent years, several studies underlined the relevance of the CRT beyond the classical deliberation-intuition trade-off (Baron et al., 2014; Mata et al., 2013; Szaszi et al., 2017). In particular, it has been linked to the tendency to use more thorough search processes (Cokely and Kelley, 2009; Cokely et al., 2009) and to the ability to accurately process and represent task-relevant information (Mata et al., 2014; Sirota et al., 2014). Furthermore, recent evidence pointed out that the CRT is related to analytical thinking (Hoppe & Kusterer, 2011), behavioral biases (Oechssler et al., 2009), probabilistic reasoning (Koehler & James, 2010; Liberali et al., 2012) and rule abstraction (Don et al., 2016), suggesting a broader involvement of cognitive reflection in intelligent behavior.

Experiment 1

Methods

Relational-inference task

In this novel task, participants were presented series of three conditional statements of the form "if A, then B" connecting pairs of symbols. Symbols represented "states of the world" whose occurrence was uncertain, while conditional relations between symbols prescribed the

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necessary occurrence of a state (e.g. B) upon the occurrence of another state (e.g. A). Importantly, conditional relations could be linked by transitive relations (for example, given the two conditionals "if A then B" and "if B then C", you can conclude that "if A then C"). Henceforth, we will refer to the three conditional statements as C1, C2 and C3. Four abstract symbols (square, circle, triangle and cross) were used to represent states (Figure 1, left panel). Using this set of items, we created 80 different relational sets. From all the possible combinations of symbols and relations, we excluded those including a specific symbol simultaneously repeated in all three antecedents or in all three consequents of the conditionals. Each configuration could contain 0, 1, 2 or 3 transitive relations connecting conditionals in up-down or down-up directions.

Each trial of the task consisted of two phases: Representation and Response. In the Representation phase (Figure 1, left panel), participants had 9 seconds to learn all the relevant pieces of information in a series before their disappearance. In the Response phase, one of the symbols presented in the Representation phase (source state) was highlighted, meaning that that state had indeed occurred. Given this novel information and the conditional relations shown in the Representation phase, participants had to select all the states (i.e. symbols) that necessarily followed the occurrence of the source state (Figure 1, right panel). There was no delay between the two phases. In the Response phase, each of the four symbols was paired with a specific response key. An intuitive interface supported the Response phase (Figure 1, right panel). Key-symbol associations remained stable along the entire experiment.[1] Symbols could be pressed in any order. Participants had the opportunity to re-press the same response-key to de-select or re-select a specific symbol. Participants were instructed that de-selecting and re-selecting symbols would not have affected their score; final selection was confirmed by

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[1] We checked for possible effects due to the position of symbols and corresponding keys in the response interface and we did not find any effect of source state (see Table 1.B1 in section 1.B.1, Appendices).

pressing the space bar and only this response was taken into account for evaluation. In sum, a trial was classified as correct if participants selected *all and only* the states that necessarily followed the occurrence of the source state and as incorrect in all other cases. Participants had unlimited time in the Response phase, and they were instructed that reaction times would not influence their final score.

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We created two different categories of relational set: linear and non-linear. In linear sets, the order of the presented triplet of conditionals was aligned with the latent relational structure (i.e. with the ordered sequence of concatenated events) (Figure 2, left panel). In non-linear sets, the underlying relational structure did not match with the order of the presented triplet of conditionals (Figure 2, right panel). The presence of non-linear trials allowed us to disentangle sophisticated from unsophisticated representation processes: sophisticated participants should indeed search for all possible relations between states in every potential direction and location, while unsophisticated participants should encode binary conditional rules independently of their higher-order relations.

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All these aspects of the task were carefully explained to participants with examples, control questions and training trials (we report full instructions and control questions in the Online Supplementary Material). In particular, we ensured that participants correctly understood all

the conditional, transitive and spatial properties of the task. Participants were provided with three 2-minute breaks (one every 20 trials). The order of trials was randomized across participants. Each trial was preceded by a fixation-point positioned in one of four possible locations outside the symbol space.

The task was made incentive-compatible by paying participants according to their proportion of correct responses (minimum 0, maximum 14 euros).

Visual search control task

The Visual search task served as a control for individual differences in visual scan efficiency. In this task, participants had to detect a target among a variable number of distractors. They were instructed to be as accurate and fast as possible, and they were reimbursed based on a scoring formula combining accuracy and reaction times (see section 1.A.2 in Appendices).

Cognitive measures

Raven Advanced Progressive Matrices Test (APM). Participants performed the Raven Advanced Progressive Matrices Test (APM). In particular, we used a 20-minute timed version of the task, which has been shown to be an adequate predictor of the untimed APM score (Hamel & Schmittmann, 2006). Participants were paid according to the number of correct responses (20 cents for each correct response, maximum 7.20 euros).

Cognitive Reflection Test (CRT). Participants answered the three questions of the CRT without any time limit. The CRT score reflected the number of correct responses in the test.

N-back task (2-back and 3-back). Participants performed a computerized version of the 2-back and 3-back task. In each of these tasks, participants were presented with a series of individual letters appearing at the center of the screen (100 letters in total) and they had to decide whether the current letter matched the one observed two (in the 2-back task) or three (in the 3-back task)

trials before. Each letter was presented for 1000 ms, followed by a blank screen for 1000 ms. At each trial, participants indicated their choice by pressing a response key for "match" or pressing nothing for "non-match". In both tasks, participants were paid according to their proportion of correct responses (min 1 euro, max 3 euros for each task).

Forward and backward digit span: Participants were asked to repeat orally series of digits in the presented order (digit span forward) or in reversed order (digit span backward). They repeated increasingly long sequences of digits until they made two mistakes.

Participants and procedure

Participants were 50 students from the University of Trento, Italy (38 females, mean age 23.16, SD 2.80). The study was approved by the local ethics committee and all participants gave informed consent. Every participant took part in two experimental sessions on consecutive days. Participants performed the different experimental tasks in fixed order.

In the first experimental session, participants completed the Relational-inference task while their eye movements were registered. After completing the Relational-inference task, participants performed the Visual search control task.

In the second experimental session, participants completed the Raven Advanced Progressive Matrices Test (APM), the Cognitive Reflection Test (CRT), 2-back and 3-back tasks and forward and backward digit span tests in fixed order. Feedback about performance and respective earnings in each task were provided at the end of the second experimental session.

Relational-inference task: eye-tracking analysis

Classification of transitions

To analyze eye movements, we defined six Regions of Interest (ROIs) in correspondence of the six symbols (see section 1.A.1.2 in Appendices). We classified transitions as eye movements from one ROI to the next.

We classified a transition as Transitive Transition (henceforth, Transitive-T) if it was suitable for detecting a transitive relation within a relational set. More specifically, we focused on transitions connecting the consequent of a conditional relation to the antecedent of another conditional, since premise integration in transitive inference is generally achieved by the compression of the repeated term in a single token (Sternberg, 1980).

We also divided transitive-Ts in linear transitive-Ts and non-linear transitive-Ts (Figure 3).

Linear transitive-Ts were those transitions suitable for detecting transitive relations in linear relational sets (up-down transitive relations between adjacent conditionals). On the contrary, non-linear transitive-Ts were coherent with an attempt to individuate transitive relations in non-linear sets (any down-up transitive relations or transitive relations connecting non-adjacent conditionals).

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Representation-building and Representation-consolidation intervals

In order to individuate the type of representation process employed by each participant, we need to segregate processes purely related to the generation of representations from mechanisms associated with retention of information in working memory. In fact, within the Representation phase, we expect 1) a first stage more oriented to information acquisition, meant to build a representation of the current relational structure and 2) a second stage more dedicated to the consolidation of information in working memory, in view of the Response phase. These

two stages should be marked by a peculiar difference in terms of cognitive load: the initial phase of information-search should require a lower memory load than the process of mnemonic consolidation of the final representation. Recent eye-tracking evidence highlighted a relation between computational load and fixation length: in particular, exploratory behavior is associated with short fixations, while higher-order processes are characterized by longer fixations (Graffeo et al., 2015; Velichkovsky et al., 1999, 2002). Moreover, several studies on gaze data revealed that exploratory behavior emerges in an initial phase of the visual analysis, while integration of information intervenes in a later stage (Castelhano et al., 2009; Unema et al., 2005). For these reasons, we expect the first stage to be characterized by shorter fixations compared to the second stage. Taking advantage of this property of gaze data, we performed several within-participant and within-trial cluster analyses using as variables of interest 1) the *fixation length (ms)* and 2) the *time point* of the fixation *(ms).[2]* Datasets included data-points from single trials in individual participants. We used a k-means cluster analysis using an algorithm based on L1 (Manhattan) distance to individuate two clusters in each dataset.[3] We performed 4000 (50 participants * 80 trials) different cluster analyses on 4000 different datasets, individuating in each trial two clusters of fixation events: an early set of fixation that we associated with the representation-building process and a later cluster of fixations related to representation-consolidation mechanisms (Figure 4). Henceforth, we will refer to these temporal phases as Representation-building and Representation-consolidation intervals. This

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[2] We used *end of fixation* instead of *start of fixation* as temporal indicator of fixation occurrence since it facilitates the detection of the temporal switch from short to long fixations by the clustering algorithm.

[3] We chose an algorithm based on L1 distance since it has been shown to be more robust to the influence of outliers compared to higher-order distance metrics including Euclidean distance and Mahalanobis distance (Sidiropoulos, 1999; Zhong et al., 2012) and to better deal with overpower of large-scale features (Loohach & Garg, 2012).

method allowed us to individuate intervals based on actual eye data of single participant in single trials. This aspect is important because it allowed us 1) not to assume any arbitrary length of the two intervals, 2) to preserve between-subject variability (differences in interval lengths across participants) and 3) to maintain within-subject heterogeneity (differences in interval lengths across trial categories).

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Attentional indices

Once having isolated a time interval closely related to representation-building mechanisms (Representation-building interval), we investigated whether we could detect distinct information-search patterns expressing sophisticated and unsophisticated representation processes. We expect sophisticated participants to explore the relational space to detect higher-order transitive relations between conditionals, while unsophisticated participants should not search for transitive relations and should encode binary rules without exploring the underlying higher-order relational complexity. We therefore individuated three attentional indices that could express whether agents searched for relational information in the Representation-building interval.

These are the three indices of interest:

1) Relational Search (RS): An agent who aims to search for all possible relations in the environment should perform a considerable number of transitions in a short time window. The Relational Search index expresses the tendency to perform a high rate of transitions in the Representation-building interval.

We calculated individuals' Relational Search indices dividing, for each trial, the total number of transitions by the duration of the respective representation-building interval. Then we calculated the average of these trial-by-trial search indices to obtain a single individual measure of Relational Search. The greater the index magnitude, the higher the rate of transitions carried out by the respective participant in the Representation-building interval.

2) Attentional Bias (AB): Since the relational structure of sets can be spatially expressed in different ways (e.g. linear and non-linear sets), searching for relations requires homogeneous distribution of attention in the entire relational space. Conversely, heterogeneous spread of attention might indicate a lack of purely exploratory behavior and suggest enhanced computation on the most-attended items, since agents tend to focus their attention on the elements they are processing (Devetag et al., 2016; Polonio et al., 2015; Rayner, 1998). The Attentional Bias index reflects the ability to distribute attention homogeneously across ROIs during the Representation-building interval.

More specifically, the present index measures the magnitude of deviation from the perfect distribution of attention (1/6 of total fixation time for each of the 6 ROIs). The Attentional Bias index was generated by calculating, for each trial, the Euclidean distance from the expected homogeneous distribution of attention across the six ROIs to the actual distribution of fixations across the ROIs. We used the average of these trial-by-trial indices of attention to express individual indices of Attentional Bias across participants. The lower the index value, the lower the distance from perfectly homogenous distribution of attention.

3) Relational Bias (RB): A participant who aims to build an exhaustive model of the relational environment should search for all the potential types of high-order relations in the current structure. In particular, agents should perform both types of transitive-T (linear and non-linear) in the Representation-building interval. The Relational Bias index expresses the ability to perform every type of transition to detect potential higher-order relations.

Since we individuated two types of linear transitive-Ts and four types of non-linear transitive-Ts (Figure 4), we calculated Relational Bias as the Euclidean distance between the actual ratio of non-linear transitive-Ts (over transitive-Ts) and the expected proportion of non-linear transitive-Ts (2/3 of the total number of transitive-Ts).[4] The lower the index value, the lower the distance from the expected distribution of linear and non-linear transitive-Ts.

Hypotheses

Expected gaze patterns in sophisticated and unsophisticated participants

Sophisticated: We expect sophisticated participants to build a representation that explicitly expresses the relational structure of the relational set. They should therefore search for every possible relation characterizing a relational set, showing a high rate of transitions in their Representation-building interval (high RS), exhibiting a homogenous distribution of attention across ROIs (low AB) and implementing both linear and non-linear transitive-Ts (low RB).

Unsophisticated: In the Representation-building interval, participants implementing an unsophisticated representation process should not search for higher-order relations linking conditional rules. We expect them to acquire and memorize triplets of conditionals in sequential order, without trying to manipulate and rearrange them in a model that resembles the actual relational structure of the trial. Such lack of pure exploratory behavior in favor of a tendency to memorize non-integrated chunks of information should slow down acquisition of information, leading to a low rate of transitions in their representation-building phase (low RS). Moreover, since sequences of only two to four digits at a time can be memorized (Cowan, 2012), they should spend a significant proportion of their representation-building phase on a

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[4] Number of transitive-Ts and of non-linear transitive-Ts were computed pooling data from all trials, since single trial data in the representation-building stage contained few occurrences of transitive-Ts (especially non-linear). Using trial-by-trial ratios, RB indices would have been noisier indicators of relational search behavior.

subset of the six elements (high AB). Finally, we predict them to perform few non-linear transitive-Ts (high RB), since their strategy requires a simple up-down, left-right sequential and ordered scan path, as expected by western cultural visual scan propensity (Abed 1991; Chua et al. 2005; Ishii et al. 2011).

Performance in the Relational-inference task

In the Relational-inference task, we expect sophisticated participants to show higher average accuracy rates than unsophisticated participants, since their comprehensive model of the relational environment should allow them to respond to the occurrence of every possible state. The performance drop of unsophisticated participants should be particularly pronounced in non-linear relational sets, since the mismatch between the latent relational structure and their internal representation should lead to a high error rate when applying transitive inference in the Response phase (Halford, 1984).

The role of working memory, fluid intelligence and cognitive reflection

After individuating two groups of participant expressing sophisticated and unsophisticated representation processes, we plan to compare measures of working memory, fluid intelligence and cognitive reflection across groups. If these cognitive abilities are involved in the emergence of a specific type of representation process, we should observe differences between the two groups: in particular, we would expect higher levels of working memory, fluid intelligence or cognitive reflection in the sophisticated group, in respect to the unsophisticated one. Moreover, it is possible that one or more of these cognitive abilities sustain processes of retention and updating of information independently of the representation process implemented. In this case, we should observe intra-group modulation of performance by these cognitive measures. This

would indicate that these constructs sustain correct recall of information and efficient update of information in the Response phase, when the source state is provided.

Results and discussion

Representation-building and Representation-consolidation intervals

To separate Representation-building and Representation-consolidation intervals, we run 4000 independent k-means cluster analyses on within-participant and within-trial fixation data using fixation length and time point of fixation as variables. On average, datasets included 22.5 data-points (fixations). The average time boundary between the two intervals was 4.37 seconds (SD = 0.65). Importantly, average fixation length in the Representation-building interval was significantly lower than the one in the Representation-consolidation interval (Representation-building, mean = 261.77 ms, SD = 53.92; Representation-consolidation, mean = 308.87 ms, SD = 92.06; Wilcoxon matched-pairs signed-rank test, $z = -5.613$, effect size $(r) = 0.79$, $p < .001$), suggesting that they express two distinct phases of information processing.

Disclosing sophisticated and unsophisticated representation processes

In order to investigate the existence of two distinct representation processes, we conducted a between-subject k-means cluster analysis on our three attentional indices. To estimate the optimal number of clusters in our dataset, we computed the gap statistics (Giancarlo et al., 2008; Tibshirani et al., 2001). Results revealed that $k = 2$ was the best solution (Table 1.B2 in section 1.B.1 in Appendices), suggesting that the heterogeneity in the three attentional indices was best explained by two types of behavior.

In Figure 5, we report results of the cluster analysis ($k = 2$, L1 as distance measures and RS, AB and RB as variables of interest). Cluster-1 (N = 25) was characterized by high RS, low AB and low RB; conversely, cluster-2 (N = 25) showed low RS, high AB and high RB, reflecting

expected differences in the process of representation generation of sophisticated and unsophisticated agents. For this reason, we will refer to cluster-1 as the sophisticated group and to cluster-2 as the unsophisticated group. Examples of visual analyses of sophisticated and unsophisticated participants are shown in Figure 6.

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A one-way Multivariate Anova with Relational Search, Attentional Bias and Relational Bias as dependent variables and group as independent factor confirmed that the two groups express significantly different behaviors in terms of attentional indices ($F (3, 46) = 46.58$, $p < 0.001$). Individual index comparisons confirmed that all three indices were significantly different across groups (RS: $z = 5.93$, $p < .001$; AB: $z = - 5.52$, $p < .001$; RB: $z = 2.86$, $p = .004$. All p values were significantly at Bonferroni corrected threshold, $p = 0.017$). Interestingly, subject classification was remarkably stable along the time course of the experiment: we ran two different cluster analyses for the first and second halves of the experiment, and we found that 88% of our participants were consistent in terms of strategy.

A possible alternative explanation of the observed differences in representation strategy concerns visual processing speed: in line with this hypothesis, participants in the unsophisticated group would show the observed attentional index levels simply due to low efficiency in scanning the relational environment. We tested this hypothesis by comparing the two groups in the Visual search task: if visual scan efficiency drove the eye-movement differences in the Relational-inference task, the sophisticated group would show higher

performance in the Visual search task. However, the two groups did not differ in any of the efficiency measures we collected (accuracy, reaction times, earnings; see Table 1.B8 in section 1.B.2 in Appendices). These results suggest that the inter-group differences observed in the Relational-inference task were not related to general efficiency in visual scanning.

Then we investigated whether the lookup patterns of sophisticated and unsophisticated participants changed along the time course of the trial depending on relational set type. We considered the proportion of non-linear transitive-Ts as measure of interest since its evolution in time should reflect the degree of understanding of the current relational structure. As shown in Figure 7, in non-linear sets, sophisticated participants accumulated evidence about the existence of non-linear transitive-Ts in the first part of the trial and, once they individuated them, maintained a stable ratio of non-linear transitive-Ts to favor consolidation of these relations in working memory. In linear sets, sophisticated agents maintained a low proportion of non-linear transitive-Ts, given their absence in this type of set. These results suggest that sophisticated agents were building a representation that explicitly expressed the relational structure of the environment. Conversely, we do not observe differences in the proportion of non-linear transitive-Ts across relational sets in unsophisticated participants, suggesting that they did not grasp the relational structure of the current environment.

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Performance in the Relational-inference task

We ran a mixed-design Anova with mean accuracy as dependent variable, group (sophisticated and unsophisticated) and relational set (linear and non-linear) as independent factors. Results show significant main effects of group ($F_{(1, 48)} = 18.20$, $p < .001$) and category ($F_{(1, 48)} =$

27.09, p < .001), and a significant interaction effect (F (1, 48) = 17.62, p < .001), indicating that the relation between performance in linear and non-linear sets differed across groups. Figure 8 shows that sophisticated groups show higher average accuracy than unsophisticated ones, who in turn exhibited a significant decrease in performance in non-linear relational sets. These results point out that sophisticated representation behavior is more effective than unsophisticated processing, especially when the relational structure underlying the current environment is implicit and not easily recognizable.

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Cognitive abilities, representation processes and performance

We tested whether sophisticated representation behavior was accompanied by higher abilities in cognitive reflection, fluid intelligence or working memory (Table 1). Tests of the six directional hypotheses (higher score for sophisticated participants in each cognitive test) were conducted using Bonferroni adjusted alpha levels of .008 per test (.05/6). The sophisticated group indeed showed higher CRT score than the unsophisticated group (one-tailed Mann Whitney U test, z = 2.508, effect size (r) = 0.35, p = .006), suggesting that cognitive reflection had an impact on the emergence of distinct representation processes. On the other hand, APM score and measures of working memory did not differ across groups (one–tailed Mann Whitney U test: APM, z = 0.20, p = .419; Forward digit span, z = 1.94, p = .026; Backward digit span, z = .253, p = 1.00; 2-back, z = -0.22, p = .412; 3-back task, z = 0.26, p = 0.397).

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To corroborate these findings, we run a stepwise backward logistic regression (Draper & Smith, 1998; Efroymson, 1960; Hocking, 1976) with group as dependent variable and all the six cognitive measures as independent variables. A low Variance Inflation Factor (VIF, Marquaridt, 1970) of 1.38 indicated no collinearity between variables (see Table 1.B3 in section 1.B.1 in the Appendices, for between-measure correlation table). Results confirmed that the CRT score was the only cognitive measure significantly predicting the type of representation process used (B = 0.78, p = .015, see Table 1.B4 in section 1.B.1 in the Appendices). Furthermore, we tested if one or more of our cognitive measures modulated within-group performance in the Relational-inference task. We observed that performance in the unsophisticated group was significantly affected by the level of fluid intelligence and backward span score (stepwise backward regression, Table 2). In the sophisticated group, performance was modulated by APM score, and marginally by working memory measures such as backward span and 2-back score (Table 2). These results suggest that fluid intelligence and working memory sustain the representation process by modulating mechanisms of retention and updating of stored information. It is not surprising that the effect of working memory is stronger in the unsophisticated group. In fact, the individuation of transitive relations in sophisticated participants could have allowed them to chunk information more efficiently in the Representation phase, decreasing memory load in the Response phase.

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Insert Table 2 here
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Causal mediation analysis

In order to understand the interplay between the type of representation process and cognitive measures in explaining task performance, we used Causal Mediation Analysis to test whether representation behavior could serve as a mediator in explaining the effect of one or more of our cognitive measures on performance in the Relational-inference task. To obtain a single and continuous measure of representation behavior that could serve as a mediator factor, we standardized and averaged our three attentional indices in a unique index (Representation Index).[5] Using the approach implemented in the "Mediation" R package (Imai et al., 2010), we first estimated a linear mediator model with Sophistication Index as dependent variable and our six cognitive measures as predictors. Only CRT score significantly predicted Sophistication Index (B = 0.40, p < .001, see Table 1.B5 in section 1.B.1, Appendices). This finding is in line with the results previously reported (Table 1 in the main text, Table 1.B4 in section 1.B.1, Appendices), indicating that cognitive reflection is the only measure differing across groups. The second step of the analysis consisted of estimating a linear outcome model with overall accuracy as dependent variable and Sophistication Index and the six cognitive measures as independent variables (Table 1.B6 in section 1.B.1, Appendices). Sophistication Index (B = 0.56, p < .001), APM score (B = 0.29, p < .001) and Backward Span (B = 0.26, p = .015) significantly predicted overall accuracy, while CRT score did not predict accuracy (B = .11, p = .324). However, running a linear regression dropping Sophistication Index as predictor, CRT score significantly predicted accuracy (B = 0.33, p = .014, Table 1.B7 in section 1.B.1, Appendices), suggesting complete mediation of Sophistication Index on the relation between cognitive reflection and performance.

Finally, we tested the statistical significance of the indirect effect. Confidence intervals were calculated using the bias-corrected and accelerated bootstrap method (BCa) (Di Ciccio &

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[5] We changed the sign of AB and RB indices in order to have a continuous index indicating sophisticated representation behavior for positive values and unsophisticated representation behavior for negative values.

Efron, 1996), a procedure specifically recommended in mediation analysis (Preacher & Hayes, 2008). As expected, the average causal mediation effect of Sophistication Index on the relation between CRT score and overall accuracy was statistically significant (p = .02, based on 10000 bootstrap samples), accounting for an estimated 68% of the total effect between CRT score and overall accuracy (Table 3).

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Insert Table 3 here
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In sum, Causal Mediation Analysis revealed a remarkable effect of cognitive reflection on representation-building processing, which in turn highly predicted accuracy in the Relational-inference task. The relationship between cognitive reflection and performance was largely due to this mediating effect.

Summary

In Experiment 1, we introduced a novel eye-tracking task to investigate the process of spontaneous generation of contingency representations. A cluster analysis on self-initiated patterns of information-search revealed the existence of two groups of participants that expressed different representation-building behaviors. Sophisticated participants searched for higher-order relational information in order to construct a comprehensive model of the environment that connected each state with every potential consequence of its occurrence. Conversely, unsophisticated participants encoded binary rules without searching for the higher-order relational properties underlying them. The emergence of these two distinct processes of representation generation led to marked differences in task performance, especially in

relational sets where the intrinsic structure of the relational environment was misaligned with the order of presentations of conditional rules.

Results from cognitive assessments analyses revealed that cognitive reflection is the only measure explaining the emergence of the two strategies. Conversely, fluid intelligence and working memory modulated intra-group performance levels but did not differ across groups. However, these results are only correlational and provide indirect evidence about the cognitive factors underlying sophisticated and unsophisticated behavior. For this reason, we ran Experiment 2 to investigate whether the emergence of the unsophisticated strategy was due to either the inability to implement the sophisticated strategy or to mechanisms of spontaneous strategy generation.

Experiment 2

In order to better understand the cognitive mechanisms underlying the emergence of sophisticated and unsophisticated representation processes, in Experiment 2 we ran two additional sessions of the Relational-inference task with a new pool of 56 participants. In session 1 (pre-treatment), participants completed the task with the same modalities of Experiment 1. In Session 2 (post-treatment), participants received additional information about the existence of the two strategies and their respective average performance rates. Then they were asked to repeat the Relational-inference task in the way they preferred. We compared pre- and post- treatment visual analyses to identify potential strategy switches that would indicate that unsophisticated representation behavior does not depend on cognitive ability or motivation, but rather on processes related to the spontaneous generation of sophisticated representation strategies.

Although we report Experiment 2 right after Experiment 1 for continuity in terms of research question, we acknowledge that Experiment 2 and Experiment 3 were run on the same

participants and Experiment 2 was run *after* Experiment 3, to avoid any interference by the manipulation included in Experiment 2 on behavior in Experiment 3.

Method

Participants and procedure

Participants were 56 students from the University of Trento, Italy (43 females, mean age 24.16, SD 4.75). The study was approved by the local ethics committee and all participants gave informed consent. Every participant took part in two experimental sessions (pre- and post-treatment) on consecutive days, performing the experimental tasks in fixed order. In the pre-treatment session, participants completed a shortened-version of the Relational-inference task while their eye movements were registered.[6] They were reimbursed according to their proportion of correct responses (minimum 0, maximum 9 euros). Instructions and control questions were the same as in Experiment 1. At the end of session 1, participants performed some of the cognitive tests we used in Experiment 1. In particular, we chose those tests that have been observed to impact on behavior in the Relational-inference task: APM, CRT and backward digit span. The modalities of administration of APM and backward digit span were identical to Experiment 1. Concerning the CRT, we used a recent multi-item version of the CRT (Primi et al., 2016) composed of six new items. Multi-item CRTs have been recently recommended to overcome limitations coming from familiarity and range restrictions, by

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[6] The new version consisted of 51 trials instead of the original 80 trials. Most of the items of the shortened-version were taken from the original one, but some new items were created to maintain the same ratio between linear and non-linear relational sets and balance the occurrence of the different symbols and source states. Participants were provided with two 1-minute breaks (one every 17 trials). All the other characteristics of the task remained unaltered.

decreasing the probability of previous exposure to the CRT's items and floor or ceiling effects (see Bialek & Pennycook, 2017; Stieger & Reips, 2016; Toplak et al., 2014).

In the second experimental session (Post-treatment), additional instructions were read to participants before repeating the Relational-inference task. We informed participants about the existence of the two strategies observed in the task (sophisticated and unsophisticated) and explained in details each of them, independently of the strategy used by the participant in the pre-treatment session (see Online Supplementary Material for full transcription of the instructions administered to participants). Moreover, participants were informed about the average performance and respective gain of participants using either the sophisticated or the unsophisticated strategy, calculated on data of Experiment 1.[7] After the administration of additional information, participants were asked to perform (for the second time) the task in the way they preferred, even implementing a strategy different from the two we reported. For the second session, 51 new items were created to avoid any potential confound due to the repetition of items of Session 1. Each new item consisted in a perfect copy of the correspondent item of session 1 in terms of relational structure of symbols, but the identity of symbols in each logical position was changed. As in session 1, participants were paid based on their proportion of correct responses (minimum 0, maximum 9 euros).

Using this manipulation, we ensured that all the participants could have access to the sophisticated strategy in the post-treatment session. Moreover, informing them about the difference in average gain between the two strategies served as a motivation for switching strategy. We aimed to analyze differences in representation behavior across sessions, to explore

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[7] Gain magnitudes of Experiment 1 were re-calibrated based on the minimum and maximum range of Experiment 2. Unsophisticated participants: 62% of correct responses, 5.58 euros on average. Sophisticated participants: 84 % of correct responses, 7.56 euros on average.

whether unsophisticated participants were prone and able to implement the sophisticated strategy.

Eye-tracking analysis

In the pre-treatment session, we replicated the analysis pipeline of Experiment 1. We first performed single-trial and single-subject cluster analyses on eye fixation data (fixation length and time point as dimensions) to distinguish between Representation-building and Representation-consolidation intervals. Then we considered data in the Representation-building interval to isolate three attentional indices: Relational Search (RS), Attentional Bias (AB) and Relational Bias (RB). These three indices served as variables in a between-subject cluster analysis to identify sophisticated and unsophisticated participants. We then compared the two groups to explore differences in performance in the Relational-inference task and in cognitive assessments such as CRT, APM and backward digit span.

In the post-treatment session, we recalculated our three attentional indices and performed a between-subject cluster analysis on these new indices, in order to investigate a potential change in the proportion of agents implementing the sophisticated or the unsophisticated strategy.

Hypotheses

We believe that the emergence of sophisticated representation behavior in Experiment 1 is driven by preferential access to deliberative processes of acquisition, binding and representation of relational information (as suggested by the high average CRT score). Coherently, we do not believe unsophisticated participants to be *unable* to implement the sophisticated strategy, but rather to express a minor disposition towards spontaneously generating it. For this reason, after repeating the task and having received additional instructions about the existence of the sophisticated strategy, we expect a large proportion of

the participants classified as "unsophisticated" in the pre-treatment session to switch strategy in favor of a more sophisticated one in the post-treatment session.

Results and discussion

Session 1: pre-treatment

In session 1 we replicated results of Experiment 1. We separated Representation-building and Representation-consolidation intervals in the Representation phase by running single-trial independent k-means cluster analyses using fixation length and time point of fixation as variables. The mean time boundary between the two intervals was 4.43 seconds (SD = 0.65). Fixation duration was shorter on average in the Representation-building interval than in the Representation-consolidation interval (Representation-building, mean = 254.59 ms, SD = 59.22; Representation-consolidation, mean = 292.95 ms, SD = 64.43; Wilcoxon matched-pairs signed-rank test, $z = -5.490$, effect size (r) = 0.73, $p < .001$), confirming a difference in cognitive processing across the two intervals.

A cluster analysis of our three attentional indices (calculated using data from the Representation-building interval) returned two groups showing the same patterns we had found in Experiment 1. Participants in cluster-1 (N = 36) showed high RS, low AB, and low RB, while cluster-2 (N = 20) exhibited low RS, high AB, and high RB, as expected by sophisticated and unsophisticated agents, respectively. We will refer to cluster-1 as the sophisticated group and to cluster-2 as the unsophisticated group. As expected, indices were significantly different across groups (Multivariate Anova, dependent variables: RS; AB; RB; independent factor: group. Effect of group: $F (3, 52) = 29.51$, $p < 0.001$).

A mixed-design Anova corroborated results of Experiment 1 in terms of relationships between group, relational set type and performance: we found significant main effects of group ($F (1, 54) = 13.29$, $p < .001$) and relational set type ($F (1. 54) = 33.022$, $p < .001$), and interaction

effect (F $(1, 54) = 15.28$, p = .025). Specifically, unsophisticated participants exhibited lower performance than sophisticated ones, especially in non-linear trials (Sophisticated, Linear: M = 0.84; Sophisticated, Non-linear: M = 0.78; Unsophisticated, Linear: M = 0.68; Unsophisticated, Non-linear: M = 0.55). Then we tested between-group differences in terms of cognitive reflection, fluid intelligence and working memory. Sophisticated participants showed a higher CRT score than the unsophisticated group (one-tailed Mann Whitney U test, z = 2.59, effect size (r) = 0.35, p = .005, significant at Bonferroni corrected threshold p = .017 (.05/3)), confirming that cognitive reflection has an effect on sophisticated representation behavior. We found a between-group effect of Backward digit span (z = 2.08, p = .019), but this effect did not survive Bonferroni correction (Bonferroni corrected threshold p = .017). APM score did not have any impact on the emergence of either sophisticated or unsophisticated behavior (z = 1.25, p = .106). The effect of cognitive reflection on representation strategy was corroborated by a stepwise backward logistic regression analysis with group as dependent variable and the three cognitive measures as independent variables, showing the CRT score was the only cognitive measure significantly predicting representation strategy (CRT, B = 0.77, p = .012. Variables excluded from the model: APM, p = .531; Backward digit span, p=.396).

We also replicated results indicating that fluid intelligence and working memory modulate intra-group performance (Stepwise backward regression. Sophisticated, APM: B = 0.45, p = .001; Backward digit span: B = 0.32, p = .013. Unsophisticated, APM: B = 0.55, p = .001; Backward digit span: B = 0.32, p = .058). Furthermore, representation strategy completely mediated the relationship between cognitive reflection and performance (Linear regression of average accuracy with CRT, APM and backward digit span as predictors. CRT effect without representation strategy included in the model: B = 0.24, p = .044. CRT effect with representation strategy included in the model: B = 0.17, p = .144. See table 2.A1 and 2.A2 in Section 2.B, Appendices).

In sum, results of Session 1 of Experiment 2 replicated the ones of Experiment 1, highlighting the existence of two groups of participants differing in terms of representation behavior. The emergence of these behaviors led to higher performance in the sophisticated group and was predicted by cognitive reflection level. In contrast, fluid intelligence and working memory did not predict the representation strategy implemented, but rather modulated performance by sustaining information maintenance and manipulation mechanisms.

Session2: post-treatment

After additional instructions about the existence of sophisticated and unsophisticated strategies, participants performed a second instance of the Relational-inference task. We performed the same analysis of Session 1 based on the new eye data, and we investigated how agents were classified after the manipulation. Interestingly, the new cluster analysis returned a large group of 49 (out of 56) participants showing attentional index levels expressing sophisticated representation behavior. Only 7 participants were classified as unsophisticated agents.

Comparing the classifications pre- and post-manipulation, we can observe that 35 participants were classified as sophisticated in both session 1 and session 2 (S-S group). 14 participants were classified as unsophisticated in session 1 and as sophisticated in session 2 (U-S group). Finally, 6 participants were classified as unsophisticated in both session 1 and session 2 (U-U group). Only 1 participant was classified as sophisticated in Session 1 and as unsophisticated in Session 2. We did not include this participant in subsequent analyses.

We are particularly interested in the U-S group, since it includes participants who shifted their strategy from unsophisticated to sophisticated in the post-treatment session. Comparing indices from these participants in session 1 and session 2, we can observe a significant difference in the direction of the sophisticated strategy for all three attentional indices (Wilcoxon matched-pairs signed-ranks test, RS: z = -2.98, effect size (r) = -0.80, p = .003; AB: z = 2.42, effect

size = 0.65, p = .016; RB, z = 3.30, effect size = 0.88, p = .001. All p values were significantly at the Bonferroni corrected threshold, p = 0.017). Moreover, the overall index shift was significantly higher in the U-S group than in the S-S group (One-way Multivariate Anova with RS, AB and RB as dependent variables and group (two levels: S-S and U-S groups) as an independent factor, $F_{(3, 46)} = 5.93$, p = .002). We did not include the U-U group in any statistical analysis due to the low number of subjects (n = 6). Nevertheless, comparing descriptive statistics of the three attentional indices pre- and post- manipulation in this group, we can see that index levels are very similar across sessions, and maintain the typical profile of unsophisticated agents (Relational search: M(S1) = -1.76, M(S2) = -1.78; Attentional Bias: M(S1) = 1.07, M(S2) = 1.40; Relational Bias: M(S1) = 1.47, M(S2) = 0.90).

These results confirm that a high percentage (70%) of unsophisticated participants switched towards the sophisticated representation strategy in the post-treatment session, suggesting that these agents are indeed capable of implementing it. Interestingly, the attentional shift in the U-S group predicted the increase in performance in the post-treatment session (Linear regression with increase in accuracy as dependent variable and average index shift (average of (post – pre) differences of RS, AB and RB indices) as the independent variable, B = 0.71, p = .043). However, despite the observed increase in performance, participants in the U-S group did not reach the average level of performance of the S-S group in the post-treatment session (U-S: M = 0.78; S-S: M = 0.90). This can be explained by the fact that participants in the S-S group had the possibility to repeat the task using and refining the same strategy, while U-S group implemented the sophisticated strategy for the first time in the post-treatment session. In line with this hypothesis, we can see that the average accuracy level of U-S participants in the post-treatment session (78%) was comparable to the one of S-S participants (80%) in the pre-treatment session (Table 4).

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Summary

In session 1 (Pre-treatment) we replicated results of Experiment 1 showing the existence of two distinct strategies in the process of generation of internal models of contingencies. Results of session 2 (Post-treatment) show that the majority of participants classified as unsophisticated in session 1 shifted strategy towards the sophisticated one, suggesting that unsophisticated agents *can* implement the sophisticated strategy. This suggests emergence of unsophisticated behavior is not primarily related to cognitive capacity, but is linked to a preferential access to it. Furthermore, it indicates that the implementation of the unsophisticated strategy in session 1 is not due to motivational aspects, at least for the majority of the agents in the unsophisticated group. If scarce motivation were the main driver of heterogeneity in Session 1, we would expect similar behavior in Session 2, given that incentives are identical in the two sessions.

Experiment 3

In Experiment 3, we investigated whether sophisticated and unsophisticated strategies can be generalized to more ecological contexts, where verbal premises express the conditional occurrence of hypothetical events in real life scenarios (Verbal-inference task). Specifically, participants had to judge the validity of verbal arguments consisting in conditional sequences of hypothetical states (see, for example, Byrne, 1989).

In contrast to the Relational-inference task, in the Verbal-inference task we did not impose any time constraint in the process of relation encoding. Moreover, participants were not required to rely on short-term memory mechanisms to perform the task. Despite the remarkable differences

between the two tasks, we wanted to test whether agents classified as sophisticated in the Relational-inference task would express more sophisticated representation behavior when building the representation of real-life hypothetical states in the Verbal-inference task. This would suggest the existence of general and context-independent strategies in the process of encoding and representation of contingencies.

Method

Verbal-inference task

Participants of Experiment 2 (n = 56) performed an additional Verbal-inference task while their eye movements were monitored. The Verbal-Inference task was performed in a different experimental session preceding both session 1 and 2 of Experiment 2. As in the previous experiments, participants were paid based on their proportion of correct responses (minimum 0, maximum 9 euros). The task consisted of 66 conditional sequences divided in three blocks. Each trial was composed of a sequence of two hypothetical conditional premises, followed by an assertion revealing the actual occurrence (or non-occurrence) of one of the previous states and a conclusion to be evaluated as valid or not valid. The two conditional premises were connected by a shared proposition, whose characteristics could return either *transitive* or *nontransitive* sequences. In transitive sequences, the shared proposition contained two identical terms; in nontransitive sequences, one of the terms of the shared proposition consisted in the negation of the other (Table 5). As in the Relational-inference task, in both transitive and nontransitive sequences, the presentation of the two statements could follow the temporal order of events (linear sets) or be misaligned with it (non-linear sets).

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Insert Table 5 here

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Possible inferences consisted in modus ponens (MP), modus tollens (MT), affirmation of the consequent (AC) and denial of the antecedent (DA). In some transitive sequences, participants were required to perform two inferences of the same type to judge the validity of the argument (e.g. MP ∴ MP). Nonetheless, in some of the nontransitive sequences, participants had to make two different inferences to express the validity of the argument (MP&DA; MT&AC).[8] Therefore, sequences differed among each other along four dimensions: linearity (linear or non-linear), transitivity (transitive or nontransitive), number of inferences to perform (one or two) and type of inference (MP, MT, AC and DA).

Feedback about performance in the Verbal-inference task was provided at the end of the entire experiment (Session 2 of Experiment 2).

Eye-tracking analysis

In order to investigate whether the sophisticated and the unsophisticated strategy would also emerge in the construction of internal models of real life hypothetical states, we explored visual patterns of information acquisition in different temporal intervals of the Verbal-inference task. First, we defined an interval in which participants encoded and integrated the conditional statements (i.e. constructing an internal model of the premises) before knowing anything about the actual occurrence of states (as in the Representation Phase of the Relational-inference task). This temporal interval, which will be referred to as Integration interval, reflected mechanisms of encoding and integration of the premises without including any inferential process

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[8] MP&DA and MT&AC trials were treated independently of the order of the two inferences. Therefore, in MP&DA trials both MP ∴ DA and DA ∴ MP are included, while MT&AC trials consist in either MT ∴ AC or AC ∴ MT sequences. We also included some fillers with obvious solutions to balance valid and invalid responses in participants. Fillers were solved with very high accuracy (97 %) and were not included in subsequent analyses.

dependent on the actual occurrence of states. To this aim, we defined six rectangular ROIs (647 x 167 pixels) around the six propositions of each argument (Figure 9). In each trial, we defined as belonging to the Integration interval every fixation data falling in one of the premise ROIs (R1-R4) before participants looked at the assertion (R5) or the conclusion (R6).

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Using data from this interval, we investigated whether sophisticated participants tended to focus more on the integration of the two conditional statements to form an exhaustive and explicit model of the relational structures underlying the premises. Specifically, we analyzed transitions connecting the two states of the shared proposition following the temporal order of events (i.e. independently of their spatial order). These transitions could indeed indicate an attempt at integrating the two conditional statements in a unitary and ordered model of the premises. We will refer to these transitions as Integrative transitions (henceforth, integrative-Ts). Integrative-Ts could be either *linear* or *non-linear*, depending on the current type of relational set (linear or non-linear). Since linear sets could not contain any non-linear transitive relation and therefore participants did not need to perform non-linear integrative-Ts, our eye-tracking analysis focused on non-linear sets.

Then we considered as "Judgment interval" every fixation following the first attendance of either the assertion or the conclusion, until the response was made. The Judgment interval reflected the inferential processing sustaining the judgment of the validity of the argument given the information about the actual occurrence (or non-occurrence) of one of the states and the conclusion to be evaluated. In this interval, we investigated allocation of attention and cognitive resources to specific propositional elements in sophisticated and unsophisticated

agents. In particular, we focused on those hypothetical states of the premises whose relationship had to be judged: the state (of the premises) whose occurrence has been revealed in the assertion and the state (of the premises) corresponding to the conclusion to be evaluated as valid or invalid. In the Judgment interval, we will refer to these two ROIs as Judgment states (Figure 10).

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Insert Figure 10 here
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We believe Judgment states to be the key pieces of information in the reasoning process in the Judgment interval, since the validity of the argument had to be derived from the evaluation of the hypothesized relationship between the Judgment states. Therefore, in the Judgment interval, we extracted attentional patterns that could indicate deeper information processing on these propositional elements. Specifically, we tested 1) distribution of attention between the Judgment states and the other ROIs and 2) differences in depth of information processing between the Judgment states and the other ROIs. The former parameter has been operationalized by calculating the proportion of time spent in the Judgment states compared to the other four ROIs in the Judgment interval. The latter index has been calculated as the increase in fixation duration (increase in allocation of cognitive resources, see Graffeo et al., 2015; Velichkovsky et al., 1999, 2002) in the Judgment states in respect to the other four ROIs.

Hypotheses

We expect participants classified as sophisticated in the Relational-inference task (Experiment 2, pre-treatment session) to devote greater attention to the generation of an exhaustive and explicit representation of the hypothetical chain of events when compared to unsophisticated

participants. In the Integration interval, before obtaining any information about the occurrence of states, we expect them to show a higher rate of non-linear integrative-Ts in non-linear relational sets than unsophisticated participants, who in turn should move to the assertion with a less comprehensive representation of the relationship underlying the premises.

In the Judgment interval, sophisticated participants should allocate more cognitive resources to the states whose relationship has to be evaluated (i.e. Judgment states), and devote less attention to other contextual pieces of information, since they should have already built an explicit representation of the underlying relational structure. This would translate into a higher proportion of time spent on the Judgment states, as well as an increase in fixation duration in these two ROIs. On the contrary, we believe unsophisticated participants' relational representation not to explicitly express the relationship between Judgment states. Therefore, once they have encoded the information expressed by the assertion, they should sequentially attend all the pieces of information in the set in order to concatenate conditional and transitive inferences. Consequently, we predict unsophisticated participants to allocate resources more homogeneously between Judgment states and other ROIs in respect to sophisticated ones.

We also predict "sophisticated" attentional indices to modulate the ability to judge the validity of conditional arguments, since they reflect a deeper understanding of the underlying relational structure.

Results and discussion

Behavioral results

First, we tested whether linearity (linear or non-linear), transitivity (transitive or nontransitive), and number of inferences (1 or 2) modulated performance in the Verbal-inference task. A Mixed-effect logistic model (subject as random effect on all regressors) did not show any effect of linearity (B = 0.01, p = 0.939), transitivity (B = -0.12, p = 0.102) or number of inferences

(B = 0.04, p = 0.567). Given these results, we will treat performance only in terms of type of inference. Table 6 reports average performance for each type of inference (MP, AC, DA, MT, MP & DA, MT & AC).

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Representation behavior in the Verbal-inference task

In the Integration interval, we tested whether sophisticated agents (as classified in the Relational-inference task) exhibited a higher tendency to integrate premises in a unitary model of the relational environment. We indeed observed that sophisticated agents showed a higher ratio of non-linear integrative-Ts in the Integration interval of non-linear sets when compared to unsophisticated ones (one-tailed Mann-Whitney U test: $z = 1.76$, effect size (r) = 0.79, r = 0.24, p = .039), suggesting that they focused more on the integration of conditional statements in a relationally explicit model *before* moving to the assertion. In order to describe this effect, in Figure 11 we plotted the temporal evolution of the proportion of non-linear integrative-Ts in the Integration interval of non-linear trials for sophisticated and unsophisticated participants. Sophisticated and unsophisticated agents showed similar proportions of non-linear integrative-Ts in the first seconds of information accumulation, due to an initial reading of the premises. However, after a few seconds of accumulation of evidence about the relational structure of the environment, sophisticated agents significantly increased their rate of non-linear integrative-Ts. In sum, sophisticated participants detected the non-linearity in the relational structure and focused on the integration of the two conditional statements to build a comprehensive model of the hypothetical scenario.

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Afterwards, we compared attentional indices in the Judgment interval across groups. Results show that sophisticated agents spent more time on the Judgment states (one-tailed Mann-Whitney U test: z = 1.91, effect size (r) = 0.26, p = .027) and showed a higher increase in fixation duration in the Judgments states (one-tailed Mann-Whitney U test: z = 2.05, effect size (r) = 0.27, p = .021) than unsophisticated ones. Interestingly, the attentional index in the Integration interval predicted the level of indices in the Judgment interval (Table 7), suggesting that the tendency to integrate premises in a unitary relational model during integration was associated with an enhanced attentional focus on key pieces of information during the validity judgment.

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Insert Table 7 here

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Representation behavior and performance in the Verbal-inference task

Although the proportion of non-linear integrative-Ts in the Integration interval predicted the level of the attentional indices in the Judgment interval, it did not have a direct impact on performance (Table 3.A1 in section 3.A, Appendices). We therefore tested the hypothesis that patterns of information acquisition *in the Judgment interval* predicted performance in the task. Since proportion of time spent on the Judgment states and increase in fixation duration in these ROIs were highly correlated (Spearman's rank correlation, r = 0.64, p < .001), we ran a stepwise backward regression with the two indices as independent variables and mean overall accuracy in the Verbal-inference task as the dependent variable to select the best predictor

among the two. Results show that increase in fixation duration was excluded from the model (p = .343), while the proportion of time spent in the Judgment states had an impact on performance (B = 0.43, p = .001). Therefore, we used the latter variable as an indicator of behavior in the Judgment interval to explore its effect on performance. We ran a multivariate regression with the six inference categories as dependent variables and proportion of time spent in the Judgment states as the independent variable, and we found that the attentional index predicted higher performance in AC, DA, MT&AC and MP&DA inference categories (Table 8).

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Finally, we tested whether cognitive measures such as cognitive reflection, working memory and fluid intelligence modulated performance in the Verbal-inference task. We ran a stepwise backward regression with mean overall accuracy in the Verbal-inference task as the dependent variable and APM score, CRT score and backward digit span as independent factors. Results indicated that working memory, as reflected by the backward span, predicted performance in the task (B = 0.38, p = .005, see also Table 3.A2 in section 3.A, Appendices for individual inference type analysis), while cognitive reflection and fluid intelligence levels were unrelated to mean accuracy (APM, p = 0.86; CRT, p = 0.16). This result is consistent with several studies showing correlations between working memory capacity and reasoning, for instance in the evaluation of syllogistic arguments (Capon et al., 2003; Copeland & Radvansky, 2004; Gilhooly et al., 1993, 1999; Kyllonen & Christal, 1990). Nonetheless, the association between working memory abilities and validity judgments in syllogistic arguments is in line with several

theories of syllogistic reasoning (Fisher, 1981; Johnson-Laird, 1983; Johnson-Laird & Byrne, 1991; Sternberg & Turner, 1981).

Summary

Results of Experiment 3 indicate that heterogeneity of performance in the Verbal-inference task is linked to the amount of cognitive resources allocated to the Judgment states in the Judgment interval, which is in turn predicted by the tendency to integrate premises in a unitary and explicit representation of the hypothetical scenario in the Integration interval. All these indices are associated with the emergence of either sophisticated or unsophisticated behavior in the Relational-inference task, suggesting the existence of general, context-independent strategies in building relational representations of contingencies.

General discussion

In three eye-tracking experiments, we investigated individual differences in the generation of internal representations of interrelated contingencies. In Experiment 1 and 2 we introduced a novel Relational-inference task with symbolic content, while in Experiment 3 participants had to judge the validity of arguments in verbal conditional sequences expressing real life hypothetical situations. Taken together, results of the three experiments revealed the existence of two strategies for building relational models of contingencies. Sophisticated participants spontaneously tended to construct a sequential ordered model of interrelated events, generating a mental representation that explicitly expressed the relational structure of the environment. Conversely, unsophisticated agents encoded binary conditional relations among states without grasping the underlying relational complexity.

Several insights from the three experiments unravel the cognitive nature of this heterogeneity. Results from analyses of cognitive measures across our two groups in the Relational-inference task suggest that cognitive abilities such as fluid intelligence and working memory do not have a crucial role in the process of representation strategy generation. These results are in line with recent studies investigating the emergence of different strategies in categorical learning (Little & McDaniel, 2015; Goldwater et al. 2018). These studies underlined the existence of agents either memorizing simple feature-based rules or encoding higher order relations between elements. In both studies, fluid intelligence did not predict learning strategy, even though it modulated learning rates. Moreover, evidence about the existence of a relationship between learning strategy generation and working memory capacity is inconsistent across studies (see McDaniel et al., 2014; Little & McDaniel, 2015).

Importantly, unlike fluid intelligence and working memory, cognitive reflection robustly predicted the type of representation process applied. Cognitive reflection traditionally expresses the tendency to implement either deliberative or reflexive processes (Frederick et al., 2005, Travers et al., 2016). Moreover, it has been recently associated with accuracy in processes of information search (Cokely et al., 2009; Cokely and Kelley, 2009) and representation of task-relevant information (Mata et al., 2014; Sirota et al., 2014). In line with these findings, high cognitive reflection levels may reflect a preferential access to more deliberative representation processes (Osman, 2004), which leads to the generation of more sophisticated strategies in task resolution. Moreover, it may suggest that the emergence of either sophisticated or unsophisticated behavior in representation-building processes represents a more malleable thinking disposition, rather than an unmodifiable cognitive ability (for discussions on these issues, see Campitelli & Labollita, 2010, Toplak & Stanovich, 2002).

This interpretation is supported by the results of Experiment 2, which show that the majority of participants classified as unsophisticated in the pre-treatment session switched towards

sophisticated behavior in a repetition of the task (post-treatment session), after having received additional information about the existence of sophisticated and unsophisticated strategies and their respective efficacy rates in the task. These findings confirmed that most of our participants were cognitively able to build ordered representations of sequential events, but only reflective agents had a spontaneous and direct access to sophisticated representation processing when receiving relational information about conditional occurrence of hypothetical states. However, feedback, additional instructions or simple practice can trigger analytical and deliberative processing that overcomes initial intuitive strategies (Ball, 2013), in line with two-stage reasoning process theories (e.g. Evans, 1984, 2006).

Nevertheless, Experiment 3 revealed that heterogeneity in representation behavior emerges spontaneously when agents reason about real life conditional sequences of events (Verbal-inference task). In particular, participants classified as sophisticated in the Relational-inference task (Experiment 2, pre-treatment) showed a higher tendency to integrate between-state relations in an exhaustive model of contingencies before searching for information about the actual occurrence events in the Verbal-inference task. On the contrary, unsophisticated agents were more prone to encode minimal units of relational information and start the inferential process without having built a model explicitly expressing direct and indirect consequences of states. This result is extremely important because, in the Verbal-inference task, the encoding of hypothetical states was not constrained by time or short-term memory limitations, indicating the existence of a spontaneous tendency to integrate relational information about contingencies in a coherent and exhaustive model of the relational space. This tendency also predicted behavior during the validity judgment, once information about the occurrence of a state and the conclusion to be evaluated had been attended. Specifically, participants who had already integrated premises in a comprehensive model (i.e. sophisticated participants) selectively allocated cognitive resources on the hypothetical states whose relationship had to be evaluated

(assertion and conclusion). This is consistent with reasoning with mental models (Johnson-Laird, 1983; Johnson-Laird, 2010), which predicts the generation of counterexamples to the hypothesized relationship between the states whose relationship has to be evaluated as valid or invalid. On the contrary, unsophisticated participants allocated resources more homogenously across ROIs after attending the assertion and the conclusion, suggesting that they had a less comprehensive representation of the underlying relational structure when starting inferential processing. This difference in resources allocation explained part of the heterogeneity in performance in the Verbal-inference task, showing preliminary evidence about the role of attention and representation processes in reasoning with conditional sequences.

We believe that the results of this study provide novel insights about the way agents encode and represent relational information about contingencies. Since these processes are crucial in several areas of investigations, including learning, decision-making and reasoning, we hope that our results would fuel further research into the role of representation-building functions in explaining the heterogeneity underlying higher cognition.

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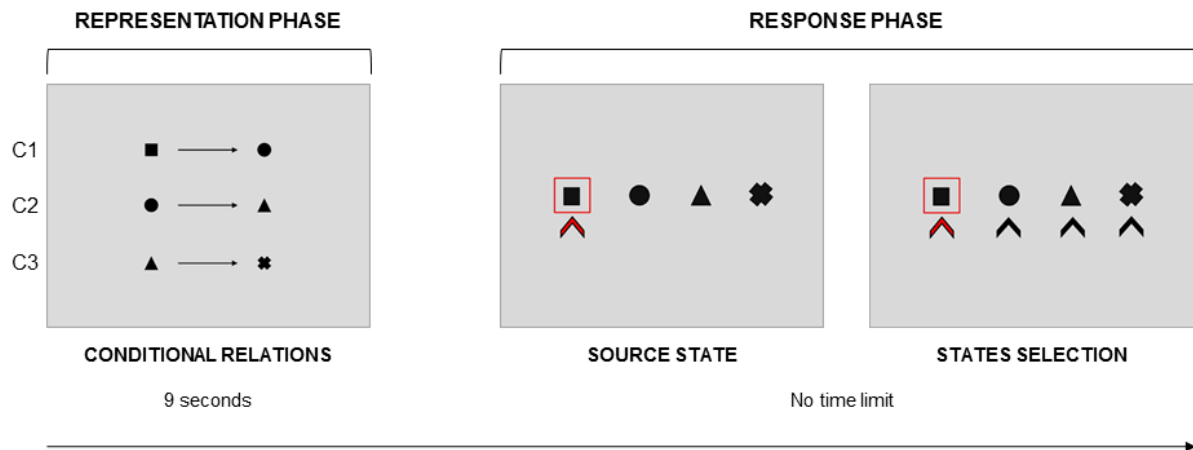
Figures

Experiment 1

Figure 1. Relational-inference task. In the Representation phase (left panel), participants observed for 9 seconds three conditional statements (C1, C2, C3) connecting abstract symbols (states). In the Response phase (right panel), they had to select all the states that necessarily followed the occurrence of one of the symbols presented in the Representation phase (source state, highlighted by a (red) square and a (red) selection mark). In the current example, participants should have chosen all three remaining symbols (circle, triangle and cross) given "square" as source state.

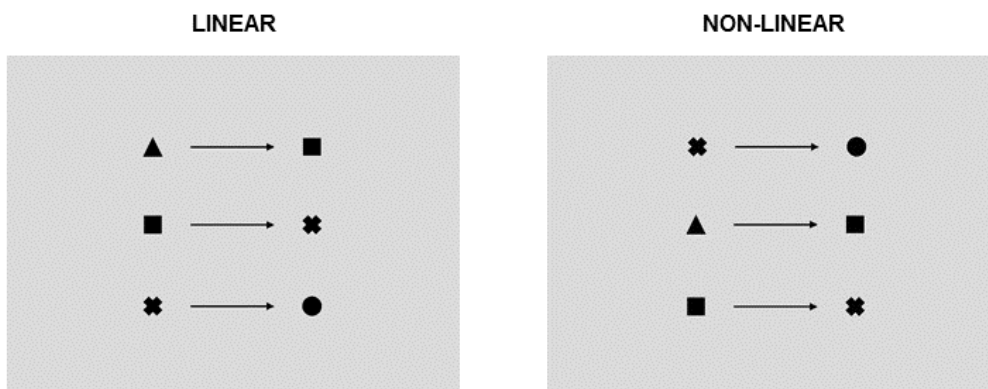*Figure 2. Types of symbol configuration in the Relational-inference task. In linear trials (left panel), the spatial order of conditionals (from up to down) matched the underlying relational structure (triangle → square → cross → circle). In non-linear trials (right panel), this was not the case: in fact, the up-down spatial order of conditionals did not match the current relational structure (triangle → square → cross →, circle).*
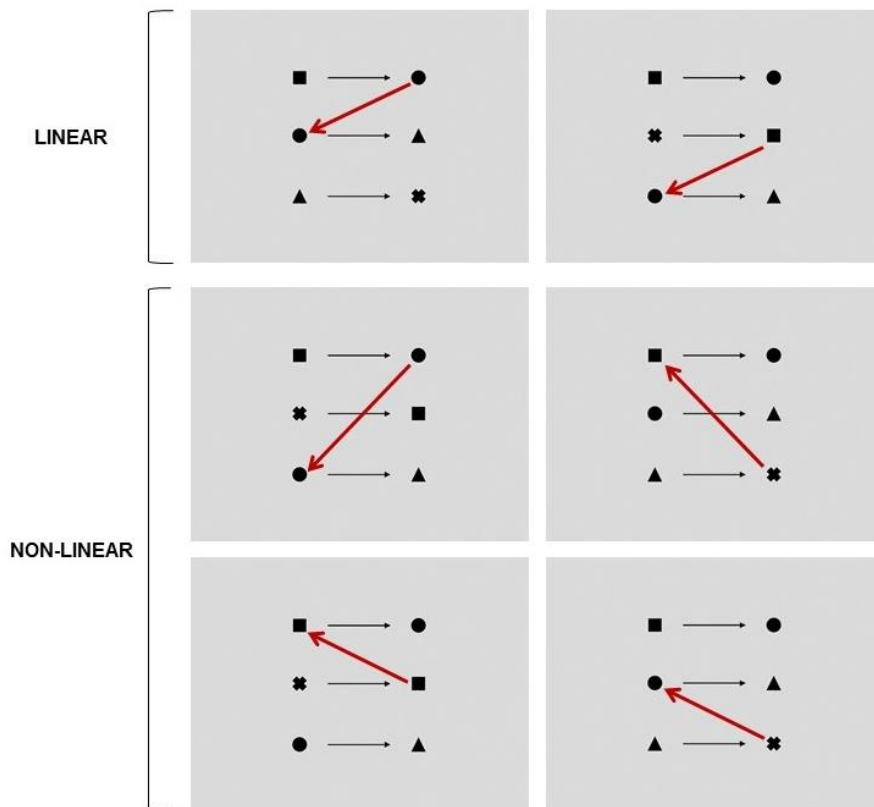
Figure 3. Depiction of the six possible transitive-Ts (arrows), grouped in linear and non-linear transitive-Ts.
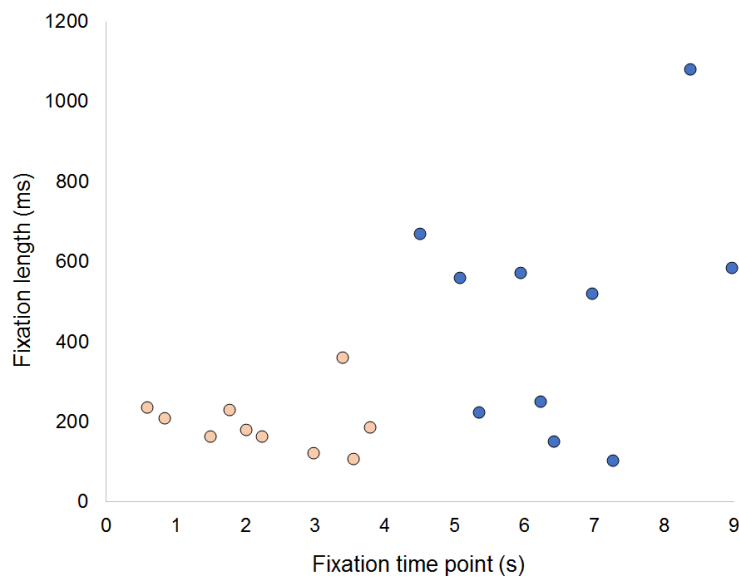
Figure 4. Example of cluster analysis on eye-tracking data from one trial of a single participant. Points represent fixations, performed in precise time points within the trial (x-axis) and characterized by specific lengths (y-axis). Colors of the points express the results of the cluster analysis: an early cluster of short fixations (orange (light gray) dots), Representation-building interval) and a later set of longer fixations (blue (dark gray) dots), Representation-consolidation
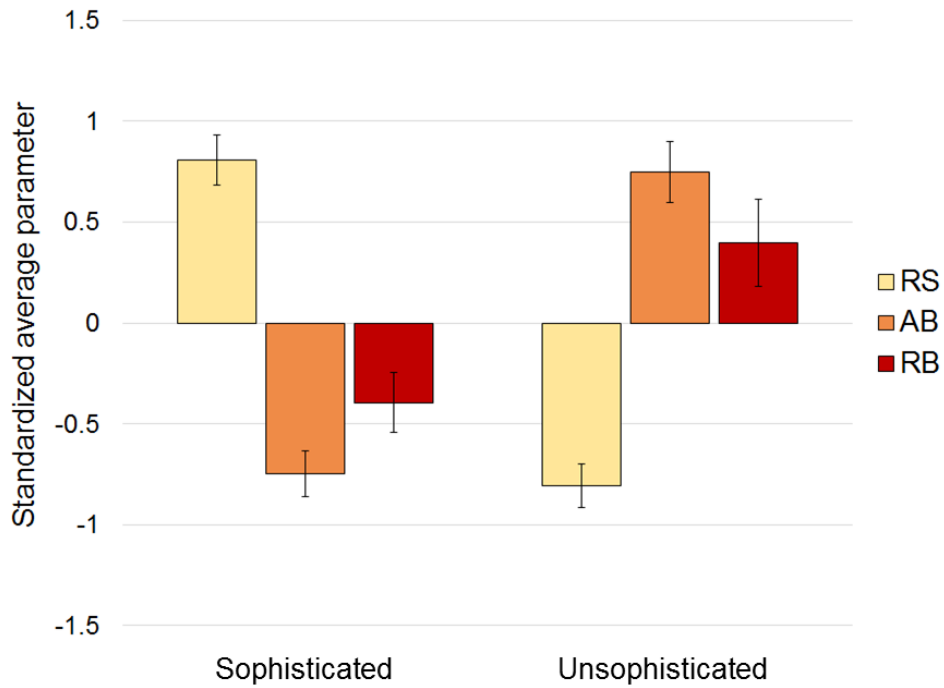
Figure 5. Bar graph of standardized indices of visual analysis in the two clusters of participants.
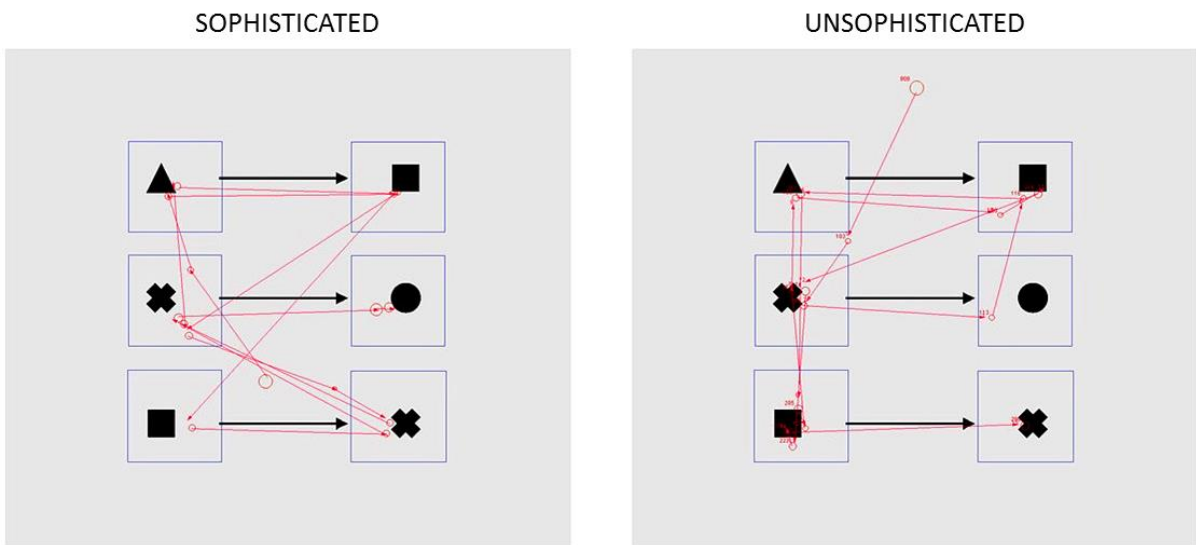
Figure 6. Examples of visual analysis of sophisticated and unsophisticated participants in the Representation-building interval. The sophisticated participant (left panel) performed a high number of transitions (red arrows), distributed her fixations rather homogeneously across ROIs (red circles) and performed both linear and non-linear transitive-Ts (as visible from the direction of arrows). The unsophisticated participant (right panel) exhibited a lower number of transitions, her attention was more focused on the top-left ROIs and did not perform any non-linear transitive-Ts.
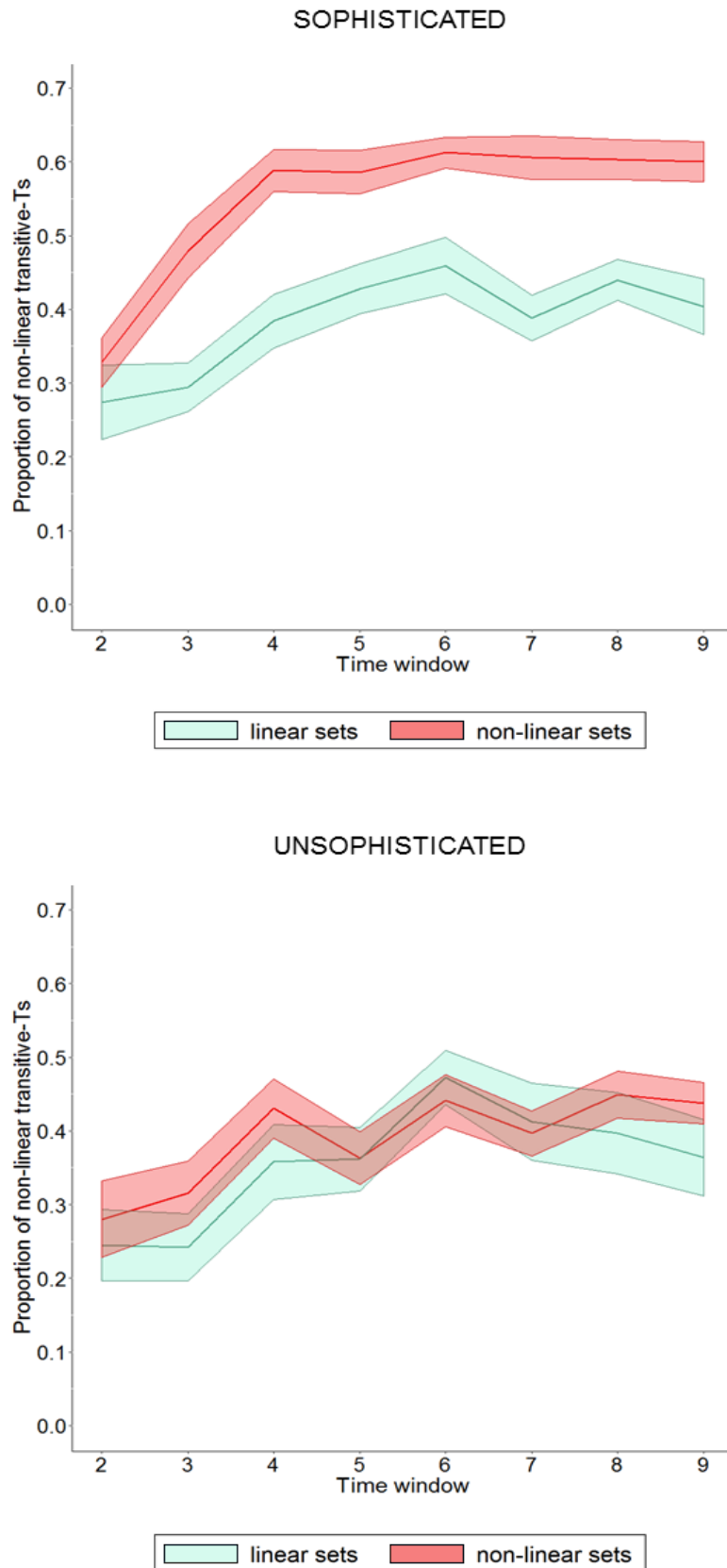
Figure 7. Time course of proportion of non-linear transitive-Ts by trial category. We considered time windows of 1 second. The first time window (0-1s) was discarded from the plot because of the extremely low number of transitive-Ts in this time interval (0.004% of the total number of transitive-Ts). Filled areas around lines represent standard error of the mean.
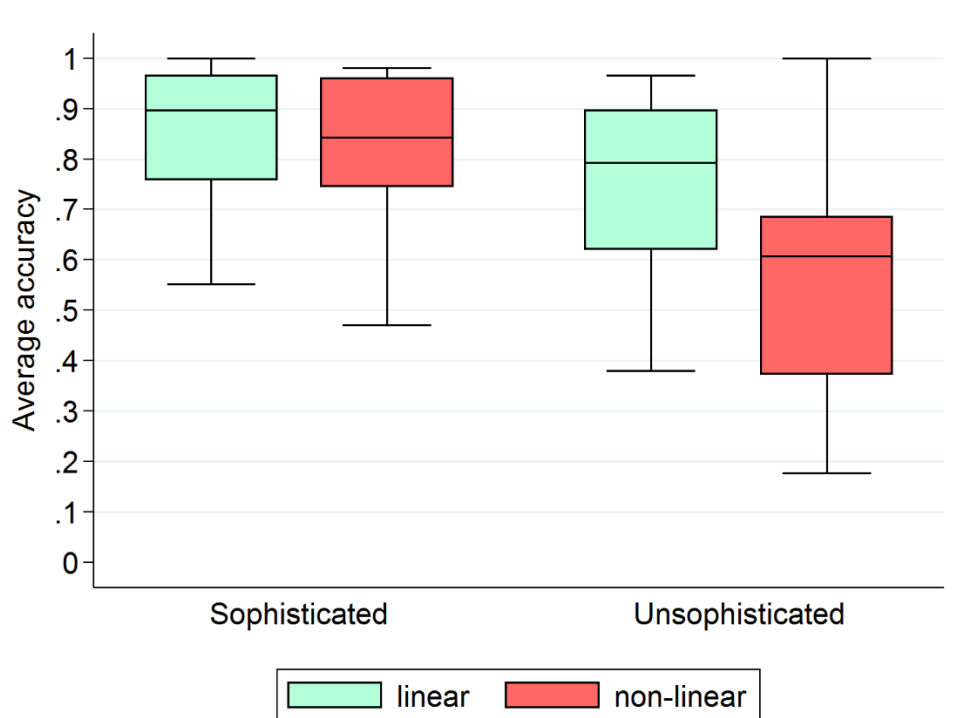
Figure 8. Boxplots of mean accuracy for the two groups in the two types of relational set.

Experiment 3
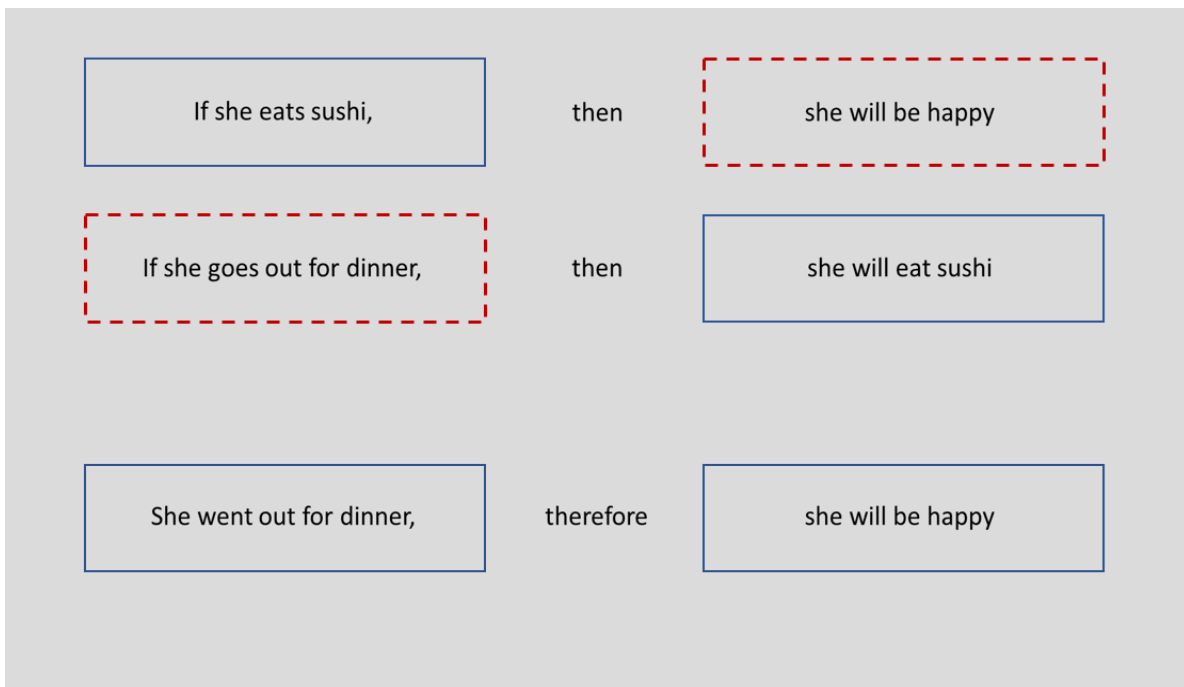
Figure 9. Example of trial with ROIs (square boxes around propositions, not shown to the participants) used for eye-tracking analysis. R1-R4 constitute the premises of the argument, and fixation falling in these ROIS before any fixation occur in R5-R6 are included in the Integration interval. In this example, dotted (red) ROIs represent the shared proposition.
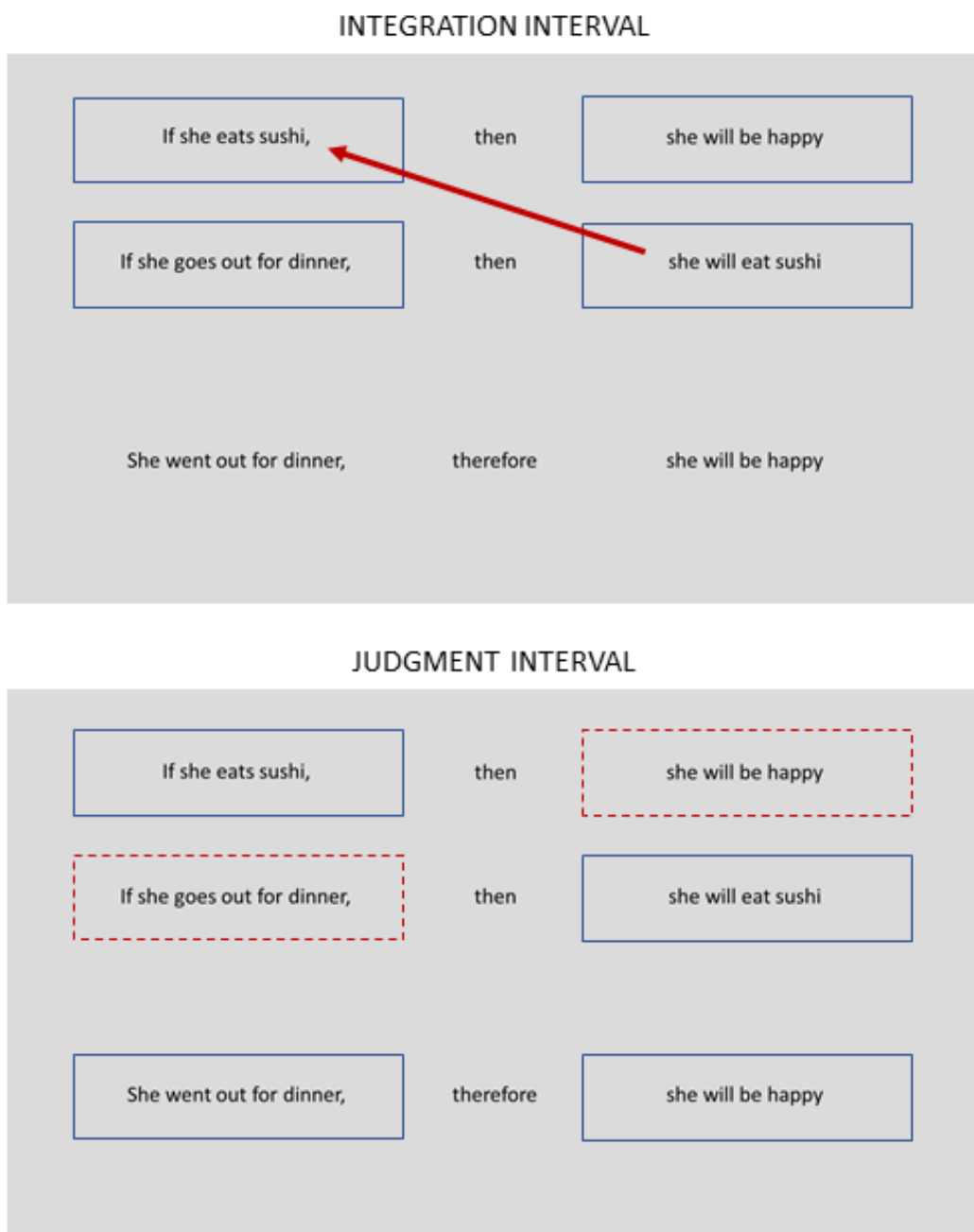
Figure 10. Eye-tracking analysis in the Integration interval and in the Judgment Interval. In the Integration interval (upper panel), before participants have acquired information about the occurrence of states and inference to evaluate, we focused on non-linear integrative-Ts (red (dark gray) arrow) in non-linear relational sets, reflecting the attempt to individuate a non-linear transitive relation between the states of the premises (square ROIs).

In the judgment interval (lower panel), once participants have looked at the assertion or the conclusion, we focused on distribution of attention and depth of information processing in the Judgment states (dotted (red) ROIs) in comparison to the other four ROIs (solid (blue) ROIs).
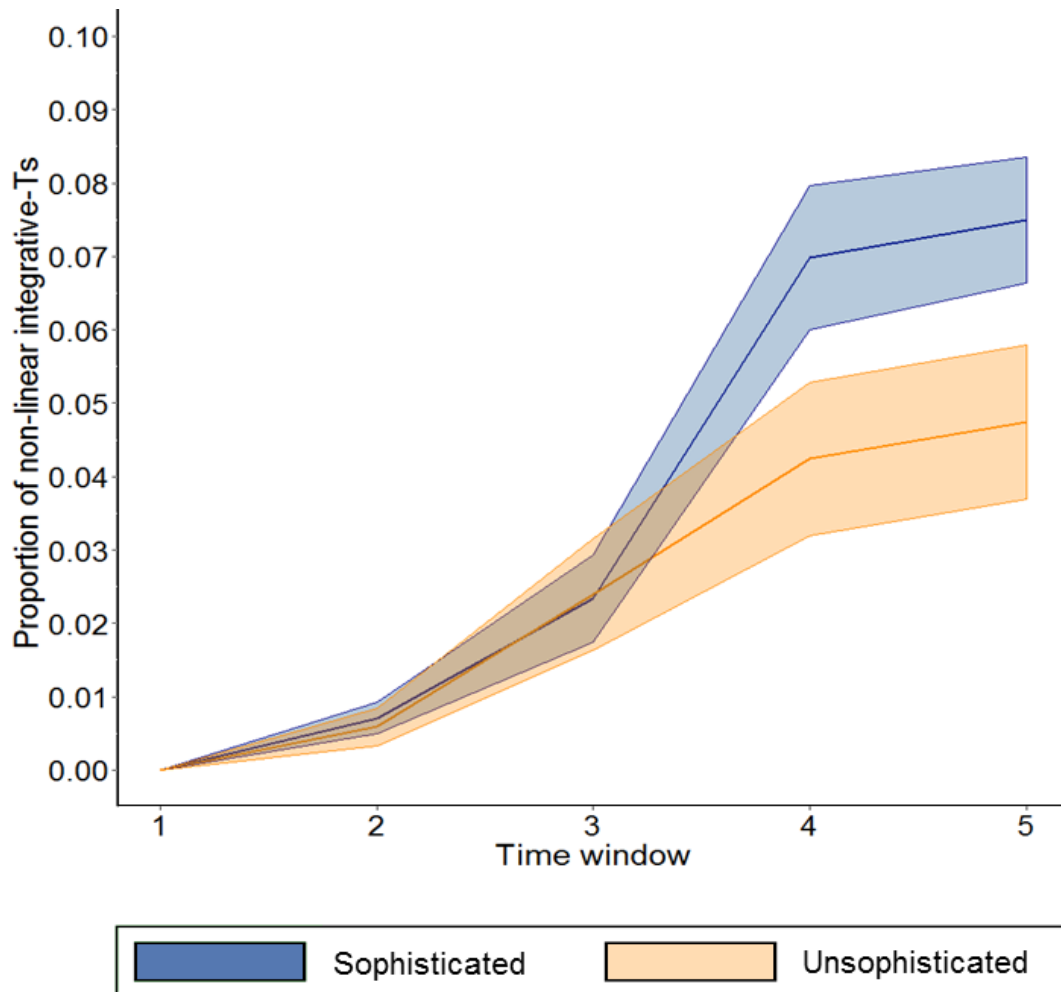
Figure 11. Time course of proportion of non-linear transitive-Ts (over the total number of between-ROI) transitions by group in the Integration interval of non-linear trials. Fixation distribution was normalized across trial time by assigning fixations to five homogeneous intervals based on total number of fixations in the Integration interval of that specific trial. In this way, each trial was characterized by five temporal intervals containing equivalent numbers of fixations. Trial-by-trial proportions of transitions were averaged for each participant and then individual time courses were averaged across participants. Filled areas around lines represent between-subject standard error of the mean.

Tables

Experiment 1

Group	N. obs.	CRT	APM	Forward digit span	Backward digit span	2-back	3-back
Sophisticated	25	1.84 (1.07)	21.24 (3.71)	6.64 (1.08)	5.4 (1.15)	0.85 (0.09)	0.72 (0.09)
Unsophisticated	25	1.04 (1.06)	20.88 (4.36)	6 (1.12)	5.24 (1.13)	0.86 (0.06)	0.72 (0.08)
TOTAL	50	1.44 (1.13)	21.06 (4.01)	6.32 (1.13)	5.32 (1.13)	0.85 (0.08)	0.72 (0.09)

Table 1. Summary statistics (average and standard deviation, in brackets) of the six cognitive tests administered to participants divided by group (row 1 and 2) and collapsed (row 3).

Overall accuracy	B	SE	t	p	95 % CI	
Sophisticated group						
APM	0.32	0.12	2.79	.011	0.08	0.56
Backward span	0.19	0.11	1.79	.087	- 0.03	0.41
3-back	0.20	0.10	1.94	.066	- 0.01	0.41
N. obs.	25					
Unsophisticated group						
APM	0.41	0.13	3.15	.005	0.14	0.69
Backward span	0.50	0.14	3.50	.002	0.20	0.80
N. obs.	25					

Table 2. Stepwise backward regression analyses of overall accuracy for sophisticated and unsophisticated groups. Only cognitive measures surviving the limit for inclusion in the model (p < .1) are reported. 2-back and 3-back measures were jointly considered for evaluation of inclusion in the model. Variables excluded from the model (sophisticated group): CRT, p=.29; digit span forward, p=.39; 2-back, p=.78. Variables excluded from the model (unsophisticated group): CRT, p=.29; digit span forward, p=.19; 2-back, p=.87. & 3-back, p=.40.

Effect	Estimated coefficient	95% CI lower bound	95% CI upper bound	p
Average causal mediation effect (ACME)	0.23	0.04	0.38	.02
Average direct effect (ADE)	0.11	-0.13	0.37	.37
Total effect	0.33	-0.02	0.61	.05
Proportion mediated	0.68	0.38	7.13	.05

Table 3. Results of Causal Mediation Analysis with Representation Index as a mediator, CRT score as independent variable and overall accuracy as dependent variable.

Experiment 2

Group	N	Pre-treatment	Post-treatment
S-S	35	0.80 (0.19)	0.90 (0.13)
U-S	14	0.60 (0.21)	0.78 (0.19)
U-U	6	0.57 (0.29)	0.64 (0.33)

Table 4. Average performance by group in Pre- and Post-treatment. Standard deviations in brackets.

Experiment 3

	LINEAR	NON-LINEAR
TRANSITIVE	If she goes out for dinner, she will eat sushi If she eats sushi, she will be happy She went out for dinner She will be happy	If she eats sushi, she will be happy If she goes out for dinner, she will eat sushi She went out for dinner She will be happy
NON TRANSITIVE	If she works, she will go home late If she doesn't go home late, she will go out She worked She will go out	If she doesn't go home late, she will go out If she works, she will go home late She worked She will go out

Table 5. Examples of items in the Verbal Conditional Sequence task

MP	AC	DA	MT	MP & DA	MT & AC
0.97	0.38	0.37	0.70	0.45	0.45

Table 6. Average accuracy by type of inference. MP, AC, DA and MT inferences include transitive (1 or 2 inferences) and nontransitive (1 inference) sequences. MP&DA and MT&AC consist of only nontransitive sequences (2 inferences). All six categories include linear and non-linear sets.

Attentional indices Judgment interval	B	SE	t	p	95 % CI	
Prop. time on Judgment states						
Proportion of non-linear integrative-Ts	0.38	0.13	3.02	.004	0.13	0.63
Increase fix. duration in Judgment states						
Proportion of non-linear integrative-Ts	0.30	0.13	2.29	.026	0.04	0.56
N. obs.	56					

Table 7. Multivariate regression with attentional indices in the Judgment interval as dependent variables and proportion of non-linear integrative-Ts as independent variable.

Mean Accuracy	B	SE	t	p	95 % CI	
MP						
Prop. time on Judgment states	0.20	0.13	1.48	.144	- 0.07	0.47
AC						
Prop. time on Judgment states	0.44	0.12	3.61	.001	0.20	0.69
DA						
Prop. time on Judgment states	0.35	0.13	2.72	.009	0.09	0.60
MT						
Prop. time on Judgment states	- 0.25	0.13	- 1.89	.064	-0.51	0.15
MP&DA						
Prop. time on Judgment states	0.40	0.12	3.18	.002	0.15	0.65
MT&AC						
Prop. time on Judgment states	0.34	0.13	2.62	.011	0.08	0.59
N. obs.	56					

Table 8. Multivariate regression with accuracy in each type of inference as dependent variables and proportion of time spent on the Judgment states as independent variable.

Appendices

1. Experiment 1

1.A Additional methods

1. A.1 Relational-inference task

1.A.1.1 Eye-tracking procedure

In the Relational-inference task, participants were seated in a chair with a soft head restraint to ensure a viewing distance of 55 cm from a monitor with 1920 x 1980 resolution. Presentation of the stimuli was performed using a custom-made program implemented using Matlab Psychtoolbox. Eye movements were monitored and recorded using a tower mounted Eyelink 2000 system (SR. Research Ontario Canada) with a sampling rate of 2000 Hz. A fixation was defined as an interval in which gaze was focused within 1 degree of visual angle for at least 100 ms (Manor and Gordon, 2003). Calibration of the eye-tracking was repeated at the beginning of each block (4 times in total). The calibration phase was repeated until the difference between the positions of the points on the screen and the corresponding eye locations was less than 1°. We used a 13-points custom calibration: points were placed at the center of each of the six symbols, at the center of the arrows expressing conditional relations and in place of the four possible positions of the fixation point.

After the calibration phase, a validation phase was executed to make sure that the calibration had been accurate. The position of each point in the validation phase was identical to the one in the calibration phase. Re-calibrations and re-validation were performed if these had been unsuccessful. Moreover, before the beginning of each trial, a drift correction procedure was introduced to force participants to look at the current location of the fixation point. More precisely, stimuli were presented after the fixation point was fixated for 300 milliseconds. The first fixation on each trial was discarded from analysis because its length and spatial location

could be biased by the previous fixation point. Stimuli were placed at optimal distance between each other in order to precisely distinguish goal-directed saccades and fixations.

1.A.1.2 Eye movements data analysis

In order to analyze eye movements of participants, we defined 6 Regions of Interest (ROIs) centered in each of the six symbols. ROIs had a squared shape with a size of 200 pixels. We discarded every fixation that was not located inside any ROIs. Although a large part of the screen was not included in any ROI, the vast majority of fixations (92.1 %) fell inside the ROIs.

1.A.2 Visual search control task: experimental design

In this task, participants had to detect as fast as possible a target among several distractors. The target element was a letter T and was actually present in the array in half of the total 120 trials. Distractors (letter L) as well as Target letter were randomly located in the full screen space (Figure 1.A3); the number of stimuli in each trial could be either 16, 20, or 24. In each trial, participants were asked to judge whether the Target letter was present or not, pressing the respective keys on the keyboard (P = present; Q = absent). They were instructed to be as accurate and fast as possible and the task was made incentive-compatible by paying participants based on both accuracy and reaction times. In particular, participants received 0.07 euros for each correct trial, from which we subtracted 0.01 euro for each second used to respond. For example, if a participant gave a correct response in 2.37 seconds, she obtained 0.0463 euros in that trial. In case of an incorrect response, the participant received 0 euros. The final outcome of each participant was the sum of the trial-by-trial earnings. Participants were provided with a break (up to 2 minutes) every 40 trials (two breaks in total).
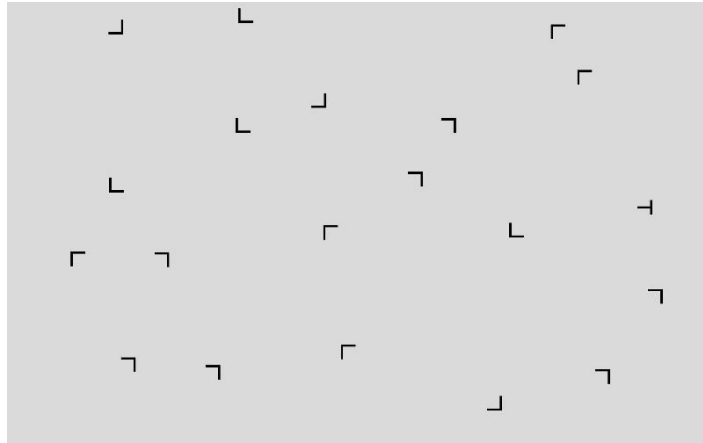
Figure 1.A1. Example of the visual search task (target (T) present).

1.B Additional results

1.B.1 Relational-inference task

Overall accuracy	B	SE	z	p	95 % CI	
Source state	.044	.035	1.25	.212	-.025	.113
N. obs.	4000					
N. independent obs.	50					

Table 1.B1. Mixed effect logistic model with trial accuracy as dependent variable, trial source state as independent variable and participant as random effect. We did not find any effect of source state on accuracy.

	Number of clusters (k)				
	1	2	3	4	5
Gap statistics	0.224	0.258	0.174	0.158	0.120

Table 1.B2. Gap statistics for different number of clusters (k: 1-5) based on 10000 Monte Carlo bootstrap samples. The value of gap that best explained data is 2.

Cognitive measure	CRT	APM	Forward digit-span	Backward digit-span	2-back	3-back
CRT	1.00					
APM	0.34	1.00				
Forward digit-span	0.39	0.22	1.00			
Backward digit-span	0.40	0.11	0.49	1.00		
2-back	0.21	0.30	0.25	0.20	1.00	
3-back	0.12	0.20	0.13	0.07	0.58	1.00

Table 1.B3. Correlation table of our six cognitive measures.

Group	B	SE	z	p	95 % CI	
CRT	0.78	0.32	2.44	.015	0.15	1.41
N. obs.	50					

Table 1.B4. Stepwise backward regression analysis of group (sophisticated or unsophisticated). Only cognitive measures surviving the limit for inclusion in the model (p < .1) are reported. Measures excluded from the model: APM, p=0.56; digit span forward, p=0.22; digit span backward, p=0.24; 2-back, p=0.16; 3-back, p=0.59.

Causal mediation analysis

Sophistication Index	B	SE	t	p	95 % CI	
CRT	0.40	0.15	2.70	.010	0.10	0.70
APM	0.03	0.14	0.20	.839	-0.25	0.31
Forward digit-span	0.24	0.15	1.60	.116	-0.62	0.54
Backward digit-span	0.05	0.15	0.33	.746	-0.26	0.36
2-back	-0.25	0.15	-1.66	.105	-0.55	0.05
3-back	0.05	0.15	0.31	.759	-0.25	0.34
N. obs.	50					

Table 1.B5. Linear model of Representation index with our six cognitive measures as independent variables. This regression will serve as mediator model for causal mediation analysis.

Overall accuracy	B	SE	t	p	95 % CI	
Sophistication Index	0.56	0.10	5.47	< .001	0.36	0.77
CRT	0.11	0.11	1.00	.324	-0.11	0.33
APM	0.29	0.08	3.02	.004	0.09	0.48
Forward digit-span	-0.17	0.10	-1.65	.106	-0.38	0.04
Backward digit-span	0.26	0.10	2.55	.015	0.05	0.47
2-back	0.08	0.10	0.76	.452	-0.13	0.29
3-back	0.15	0.10	1.47	.149	-0.05	0.35
N. obs.	50					

Table 1.B6. Linear model of overall accuracy with Representation Index and our six cognitive measures as independent variables. This regression will serve as outcome model for causal mediation analysis.

Overall accuracy	B	SE	t	p	95 % CI	
CRT	0.33	0.13	2.57	.014	0.07	0.59
APM	0.30	0.12	2.47	.018	0.06	0.55
Forward digit-span	-0.04	0.13	-0.28	.780	-0.30	0.23
Backward digit-span	0.29	0.13	2.18	.035	0.02	0.56
2-back	-0.06	0.13	-0.46	.645	-0.32	0.20
3-back	0.17	0.13	1.34	.188	-0.09	0.43
N. obs.	50					

Table 1.B7. Linear model of overall accuracy with our six cognitive measures as independent variables. The presence of a significant effect of CRT, absent when controlling for Representation index (Table 1.B5), indicates complete mediation of Representation Index on the relation between

1.B.2 Visual search control task

We collected several measures of performance: average accuracy, average reaction times and total earnings (Table 1.B8). We tested between-group differences performing a two-tailed

Mann-Whitney U test for each measure of interest. Results did not show any differences in performance across groups (accuracy, p = .83; reaction times, p = .88; earnings, p = .53).

Group	N. obs.	Accuracy	RT	RT (correct yes)	Earnings (€)
Sophisticated	25	0.91	2.02	1.43	5.44
		(0.06)	(0.48)	(0.26)	(0.39)
Unsophisticated	25	0.90	2.00	1.42	5.39
		(0.07)	(0.45)	(0.24)	(0.38)
TOTAL	50	0.91	2.01	1.43	5.42
		(0.07)	(0.46)	(0.25)	(0.38)

Table 1.B8. Summary statistics (mean and standard deviation) of measures of performance in the visual search task. None of these measures was significantly different across groups

In order to investigate whether task difficulty influenced visual scan efficiency in our two groups, we looked at the magnitude of earnings across set sizes in sophisticated and unsophisticated groups. As shown in Figure 1.B4, both groups decreased their earnings as the difficulty of the task increased. We calculated individual indices of difficulty sensitivity by subtracting earnings in trials with set size = 24 to earnings in trials with set size = 16. No difference in terms of difficulty sensitivity was found across groups (two-tailed Mann Whitney test, p = .41).
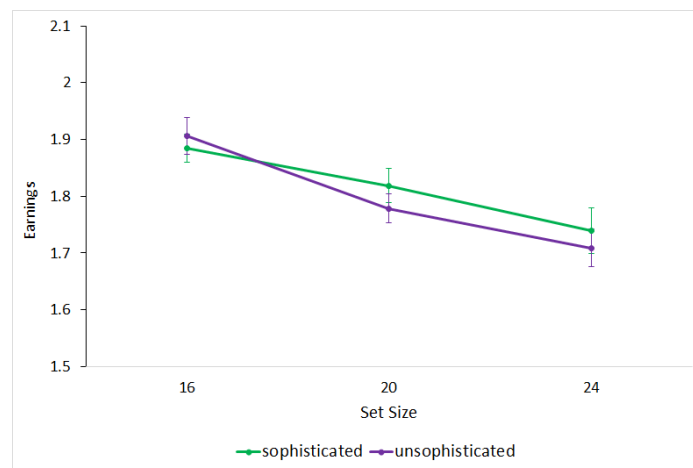

Figure 1.B1. Average earnings of sophisticated and unsophisticated groups by set size.

2. Experiment 2

2.A Additional results

Overall accuracy	B	SE	t	p	95 % CI	
CRT	0.24	0.12	2.07	.044	.001	0.48
APM	0.39	0.11	3.48	.001	.017	0.62
Backward digit-span	0.31	0.10	3.01	.004	.010	0.52
N. obs.	55					

Table 2.A1. Linear model of overall accuracy with CRT, APM and backward digit span as predictors. All the measures, including CRT, predict performance in the task. One observation missing in the backward digit span (measure not collected).

Overall accuracy	B	SE	t	p	95 % CI	
Group	-0.46	0.17	-2.66	.011	-0.80	-0.11
CRT	0.17	0.11	1.48	.144	-0.06	0.40
APM	0.41	0.11	3.88	< .001	0.20	0.63
Backward digit-span	0.28	0.10	2.81	.007	0.08	0.48
N. obs.	55					

Table 2.A2. Linear model of overall accuracy with Representation strategy (group) and our three cognitive measures as independent variables. When Representation strategy is included in the model, CRT score is no more significant, indicating full mediation of representation strategy on the relationship between cognitive reflection and performance. One observation missing in the backward digit span (measure not collected).

3. Experiment 3

3.A Additional results

Mean Accuracy	B	SE	t	p	95 % CI	
MP						
Prop. non-linear integrative-Ts	0.12	0.14	0.88	.381	-0.15	0.39
AC						
Prop. non-linear integrative-Ts	0.18	0.13	1.32	.191	-0.09	0.45
DA						
Prop. non-linear integrative-Ts	0.05	0.14	0.40	.689	-0.22	0.33
MT						
Prop. non-linear integrative-Ts	- 0.01	0.14	- 0.09	.932	-0.28	0.26
MP&DA						
Prop. non-linear integrative-Ts	0.04	0.14	0.27	.788	-0.24	0.31
MT&AC						
Prop. non-linear integrative-Ts	0.05	0.14	0.39	.695	-0.22	0.33
N. obs.	56					

Table 3.A1. Multivariate regression with accuracy in each type of inference as dependent variables and proportion of non-linear integrative-Ts in non-linear trials as independent variable.

Mean Accuracy	B	SE	t	p	95 % CI	
MP						
Backward digit-span	0.34	0.13	2.65	.011	0.08	0.60
AC						
Backward digit-span	0.26	0.13	1.98	.053	-0.00	0.53
DA						
Backward digit-span	0.35	0.13	2.66	.010	0.09	0.61
MT						
Backward digit-span	- 0.12	0.14	- 0.86	.395	-0.05	0.49
MP&DA						
Backward digit-span	0.22	0.13	1.66	.102	-0.25	0.34
MT&AC						
Backward digit-span	0.24	0.13	1.81	.076	-0.03	0.51
N. obs.	55					

Table 3.A2. Multivariate regression with accuracy in each inference type as dependent variables and Backward span as independent variable. One subject excluded from analysis (backward digit span score not collected).