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Gaze data reveal adaptive mechanisms of strategy generation in judgment and decision making

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Table of contents

Abstract

Human beings must constantly adapt to an uncertain and mutable world by generating efficient behavioral strategies to pursue their goals. The complexity of this task increases in interactive contexts, where the outcomes of our actions depend also on the choices of other agents. When the environment does not provide reliable feedback, the effectiveness of behavioral strategies rests on the ability to handle available knowledge: agents have indeed to extract relevant information from noisy signals and build an exhaustive representation of the set of potential actions and outcomes available to themselves and to others. Individual differences in the implementation of these information-processing operations may underlie behavioral heterogeneity in several judgment and decision making tasks. Here we report three eye-tracking studies revealing the existence of distinct information-processing strategies in different individuals. Study 1 explores inter-individual differences in the generation of relational representations of interdependent contingencies. In Study 2 and Study 3, we move towards social contexts to investigate the mechanisms of strategy generation underlying strategic behavior in interaction. Our findings indicate that gaze data can disclose individual differences in the process of spontaneous strategy generation in both individual and interacting settings. We also report results suggesting that the emergence of unsophisticated information-processing strategies is associated with cognitive style. Moreover, we show that the attentional mechanisms sustaining the generation of unsophisticated strategies can be reconsidered and updated under the impact of endogenous and exogenous cues revealing the existence of alternative information-processing behaviors.

1. General introduction

Information-processing and strategy generation in judgment and decision making

In our everyday experience, we often need to make decisions in mutable and uncertain environments and choose efficient behavioral strategies in order to achieve our goals. Decades of experimental research on complex human behavior have shown that agents usually depart from normative models of reasoning and decision making, describing the emerging heterogeneity from different perspectives. One of the most successful concept used to explain departures from expected “rational” behavior is *bounded rationality*, originally proposed by Herbert Simon (1957), which introduces cognitive constraints in the modelling of complex human behavior. Bounded rationality describes the process of optimization of decisions when cognitive capacity is limited, giving rise to the implementation of heuristics (Gigerenzer & Selten, 2002). Heuristics have been traditionally seen as a way to balance a trade-off between effort and accuracy by use of meta-cognitive strategy selection rules (Beach & Mitchell, 1978). In principle, theories of bounded rationality can assume full rationality of agents, once the costs of executing specific decision processes are included in their “rational” model of choice (Payne et al., 1986). If the assumption of full rationality holds, we can similarly assume that agents have a correct and exhaustive mental representation of the decision problem (Orquin & Loose, 2013). However, accumulating evidence in several domains of judgment and decision making research suggests that agents are not always fully rational (Kahneman, 2003; Oaksford & Hall, 2016) and the emergence of suboptimal strategies stem from cognitive, rather than meta-cognitive, factors. In line with this interpretation, agents may generate incorrect or inefficient task representations and build non-exhaustive models of the set of available actions and strategies. This is particularly relevant when individuals do not have the opportunity to rely on feedback about the effectiveness of their behavior: in these settings, the way in which they spontaneously handle available knowledge about the current environment has a strong impact on the strategy they generate. In particular, agents may need to extract relevant pieces of information from noisy signals, understand their relational properties and build an exhaustive representation of the set of potential actions and outcomes available to themselves. Individual differences in these information-processing functions may explain and predict a considerable part of the behavioral heterogeneity generally observed in judgment and decision making tasks. This perspective shifts the research focus on the exploration of the processes of encoding and representation of available information underlying deviations from normative models of reasoning and decision making (Ball, 2013a; Konovalov & Krajbich, 2016).

Strategy generation in interactive contexts

In several decision settings, the outcomes of our actions depend also on the choices of other agents who may be guided by different incentives and goals. These *interactive* decision settings have been extensively studied using multi-player matrix games. Matrix games consist in a set of incentives (i.e. payoffs) and a rule set for each player: the combination of players' decisions therefore determines their respective outcomes. In this context, it is important to understand others' goals and intentions to predict their actions, an ability that is referred to as "mentalizing" or "Theory of Mind" (ToM, Premack & Woodruff, 1978). In classical game theory, optimal strategic behavior has been described using the concept of Nash equilibrium (Nash, 1950), which models expected behavior of fully rational agents that have correct beliefs about the actions of the peers involved in the interaction. Nonetheless, accumulating experimental evidence has shown that agents are often non-strategic and constantly deviate from the normative Nash equilibrium strategies (Grosskopf & Nagel, 2008). In order to account for the heterogeneity observed in interactive games, behavioral models of strategic thinking such as Level-K (Crawford, 2003; Crawford et al., 2013; Nagel, 1995; Stahl & Wilson, 1995) and Cognitive Hierarchy (CH, Camerer et al, 2004; Chong et al., 2016; Ho et al., 1998) allowed more flexibility in players' beliefs, modelling behavior in terms of hierarchical levels of strategic sophistication (Nagel, 1995). These theories assume that players distribute along a hierarchy of levels of strategic thinking and best-respond to the belief that their opponents are less sophisticated than them. These hierarchical models indeed offer an elegant description of the heterogeneity observed in interactive decisions, but do not provide a cognitive explanation about the drivers of this variability. For instance, it is not clear if agents applying few steps of strategic thinking do believe that the other players are bounded rational and therefore best-respond to this belief, or they are bounded rational themselves (Goodie et al., 2012; Grosskopf & Nagel 2008). In the former case, players would use a meta-cognitive selection rule that adapts to the predicted level of the counterpart(s), whereas in the latter case the level of strategic sophistication would be bounded by cognitive factors. Concerning this "cognitive" hypothesis, it must be acknowledged that interactive games are comparable to any other decision task where agents need to take into consideration several interrelated pieces of information to form an exhaustive representation of the contingencies in the environment. Specifically, agents should consider their own incentives, the ones of the counterpart(s), and integrate them in a comprehensive representation of the interactive problem. This process of generation of a representation of the interactive scenario sustains recursive reasoning mechanisms of evaluation and prediction of others' actions and beliefs and constitutes the mean by which strategic actions are implemented (Hedden & Zhang, 2002). Coherently, if agents do not incorporate specific chunks of information (e.g. the incentives of the opponent) in their model of the strategic environment, or inaccurately integrate them with other available information, optimal game solutions could be hard to identify (Kreps, 1990). This interpretation is supported by extensive evidence showing that unsophisticated choices in games are predicted by the non-attendance of crucial information (Brocas et al. 2014, 2018; Polonio et al., 2015; Polonio & Coricelli, 2018) or by misrepresentation of payoff relationships (Devetag & Warglien, 2008). Nevertheless, it is not clear whether game misrepresentation stems from 1) the inability to perform the specific cognitive operations required to build an exhaustive and correct representation of the relational structure of the game, or 2) strategy generation mechanisms allowing the spontaneous emergence of effective representation-building strategies in absence of informative external cues. Importantly, as we will see in the next paragraph, both hypotheses can be interpreted in terms of inter-individual variability in cognitive abilities.

The cognitive factors underlying strategy generation

If individuals generate different representations and strategies in complex tasks, it is important to explore the potential sources of this heterogeneity. In particular, we may ask why some agents implement less sophisticated strategies and choices than others.

On the one hand, the psychology literature extensively relied on dual-process theories describing the existence of two different information-processing systems, one intuitive and one deliberative, often referred to as System 1 (intuition) and System 2 (deliberation) (Evans, 2003; Kahneman, 2003; Stanovich & West, 2000). The operations of System 1 are generally seen as automatic, fast, associative, implicit and effortless. System 2 is serial, slower, effortful, rule-governed and deliberately controlled (Kahneman, 2003). Although behavior is generally determined by both systems, decisions and judgments can be dominated by one system's processes (Betsch & Kunz, 2008). For example, although System 2 is involved in some measure in all types of judgment, in some instances of intuitive judgment it may be dominated by System 1. Several features of a decision context may modulate the selection of intuitive or deliberative decision strategies (Hammond et al., 1987). Moreover, it has been suggested that between-subject heterogeneity in the activation of intuitive or deliberative cognitive systems is driven by individual differences in cognitive styles (Sadler-Smith, 2004), which reflect preferred ways of processing and organizing information (Messick, 1976). Furthermore, inter-individual variability in the implementation of different cognitive systems may be explained by individual differences in the cognitive cost associated with the instantiation of either intuitive or deliberative processing (Payne et al., 1986) and by meta-cognitive factors involved the evaluation of the efficacy of the current strategy.

In line with this view, we can hypothesize that between-subject differences in information-processing strategies are rather malleable, meaning that the presence of some type of endogenous or exogenous cue providing meta-cognitive feedback about the efficacy of the current strategy may trigger the exploration of new alternative strategies. This interpretation is consistent with two-stage reasoning process theories (e.g. Evans, 1984, 2006) suggesting that differences in reasoning processes arise from the emergence of analytical and deliberative processing that overcomes initial intuitive strategies (Ball, 2013b).

On the other hand, we can hypothesize that the implementation of unsophisticated representations and strategies is driven by cognitive inability, which may reflect limitations in more stable cognitive traits such as fluid intelligence or working memory. In other words, the processes of information encoding and representation required to comprehensively understand the interactive nature of games may be overly complex or cognitively costly for some players, who may decide to decrease cognitive load and complexity by forming a simplified representation of the game structure. In line with this latter hypothesis, the presence of cues revealing the existence of better alternative strategies should not allow a successful switch towards more sophisticated behavior.

Using process-tracing to investigate strategy generation in judgment and decision making

In order to investigate individual differences in information-processing in judgment and decision making scenarios, we need to investigate the exact way in which individuals search for, manipulate and represent information. Process-tracing techniques like mouse-tracking and eye-tracking can efficiently serve this goal by allowing the exploration of dynamical information-processing mechanisms. Accumulating research has been starting to focus on the role of attention in judgment and decision-making tasks, which has been largely unexplored in the recent past. Interestingly, these methodologies have been recently combined with machine learning and modelling techniques with the aim of predicting, rather than passively describing, complex behavior (Hensher, 2010). The first advantage of these research paradigms concerns the ability to explore the dynamical properties of reasoning and decision processes, rather than treating them as static mechanisms (Konovalov & Krajbich, 2016). Using this approach, we can reach a deeper understanding of the process underlying the choice itself, by detecting the emergence of different reasoning steps characterizing the resolution procedure, or detecting temporal patterns in the process of information accumulation and manipulation underlying decisions. A second crucial benefit of process-tracing techniques concerns the capability of disclosing endogenous behavioral heterogeneity. For instance, we may observe the emergence of distinct strategies in the resolution of a task even if they lead to the same outcome. Another important feature of process-tracing research consist in the possibility to test reasoning and decision theories by comparing theory predictions and observed pattern of information acquisition during task resolution.

From a methodological point of view, mouse-tracking and eye-tracking are characterized by complementary advantages and disadvantages. On the one hand, mouse-tracking research provides an extremely accurate and noise-free measure of sequential selection and usage of available information, but introduces exogenous costs for information acquisition that may influence agent's gaze behavior and therefore bias the spontaneous process of generation/selection of strategies (Knoepfle et al., 2009). On the other hand, eye-tracking research has to deal with a noisier signal, but is indeed able to reflect an unconstrained measure of the process of information search and encoding underlying a specific task. Since this thesis aims to explore how agents spontaneously build behavioral strategies and internal representations of task environments, we have chosen eye-tracking not to pose any cognitive and procedural constraint in the way information is explored and encoded. Specifically, eye-tracking can provide several types of information about the ongoing cognitive process, starting from attentional minimal units such as fixations and saccades. Under the so-called 'eye-mind' assumption, we believe that gaze data can disclose several aspects of the cognitive processes underlying complex behavior. First, fixation analysis can reveal with extremely high accuracy which piece of information is being processed in a specific time point (Ball, 2013a). Moreover, fixation duration provides a robust index of depth of information processing or cognitive effort, with longer durations indicating greater processing difficulty (Liversedge et al. 1998; Velichkovsky et al., 1999, 2002). Furthermore, saccades are generally thought to reflect a direct an obligatory consequence of overt attentional shifts (e.g., Deubel & Schneider, 1996; He & Kowler, 1992; Hoffman & Subramaniam, 1995). These top-down attentional shifts arise when the processing of the fixated item reaches some critical level (i.e. the item has been successfully encoded), signaling to the visual system the need to prepare a motor program enabling a saccade towards the new target (Ball, 2013a). In sum, extensive evidence suggests the existence of a tight coupling between eye movements and information processing, highlighting eye-tracking as a valid tool to explore fine-grained mechanisms underlying higher cognition.

The present work

In the present thesis, we report three experimental studies investigating the emergence of information-processing strategies in different judgment and decision-making contexts. We also provide experimental evidence shading light on the cognitive mechanisms underlying the observed attentional and behavioral heterogeneity. In study 1, we explore how individuals build internal relational representations of contingencies in a novel Relational-inference task. We show that several agents use unsophisticated information-processing strategies based on the generation of an incomplete and fragmented representation of the relational complexity underlying contingencies. We also report results showing that the emergence of unsophisticated strategies does not appear to be driven by cognitive inability: unsophisticated participants can actually switch gaze patterns and strategy towards a more sophisticated representation behavior after having received additional information about the existence of alternative resolution procedures. In study 2 and 3, we move towards social settings to explore information-processing mechanisms underlying strategic behavior in interaction.

In particular, in study 2, we investigate the cognitive drivers of strategy generation in interaction by exploring the relationship between gaze patterns, strategic decisions and cognitive abilities. In study 3, we investigate the stability of attentional and behavioral strategies in normal-form games. More specifically, we explore whether unsophisticated agents change their gaze patterns and behavior strategies after exposure to alternative models of choice. Taken together, the present work provides novel evidence about the existence of crucial attentional mechanisms underlying information-processing strategy generation in judgment and decision making and reveals important insights about the cognitive sources of this variability.

2. Study 1: Gaze data reveal individual differences in relational representation processes

2.1 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 directly determining 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; 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 capacity 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 suggested by a recent theory (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 assesses the individual tendency to implement one of two types of cognitive process: those that are slower and more reflective and those executed rapidly with little conscious deliberation. In particular, a high cognitive reflection level reflects 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.

2.2 Experiment 1

2.2.1 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 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 1.1, 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 direction.[1]

Each trial of the task consisted of two phases: Representation and Response. In the Representation phase (Figure 1.1, left panel), participants had 9 seconds to learn all the relevant pieces of information in a series, before their disappearance.[2] 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 1.1, right panel). There was no delay between the two phases.

[1] Up-down transitive relations linked, by transitive property, the antecedent of a conditional located in an upper line (C1 or C2) to the consequent of a conditional in a lower line (C2 or C3). Conversely, down-up transitive relations linked the antecedent of a conditional located in a lower line (C2 or C3) to the consequent of a conditional in an upper line (C1 or C2). This aspect was carefully explained to participants to make sure they did understand that transitive relations could link conditionals both in up-down and down-up orders.

[2] The choice of the actual length of the Representation phase (9 seconds) was based on previous pilot experiments in which we tested and ensured that participants had sufficient time to encode and memorize relational information. Moreover, participants performed a visual search task that could control for differences in visual processing speed in this time interval (see next paragraph).

In the Response phase, each of the four symbols was paired with a specific response key. An intuitive interface supported the Response phase (Figure 1.1, right panel). Key-symbol associations remained stable along the entire experiment.[3] 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: in fact, final selection was confirmed by 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 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.

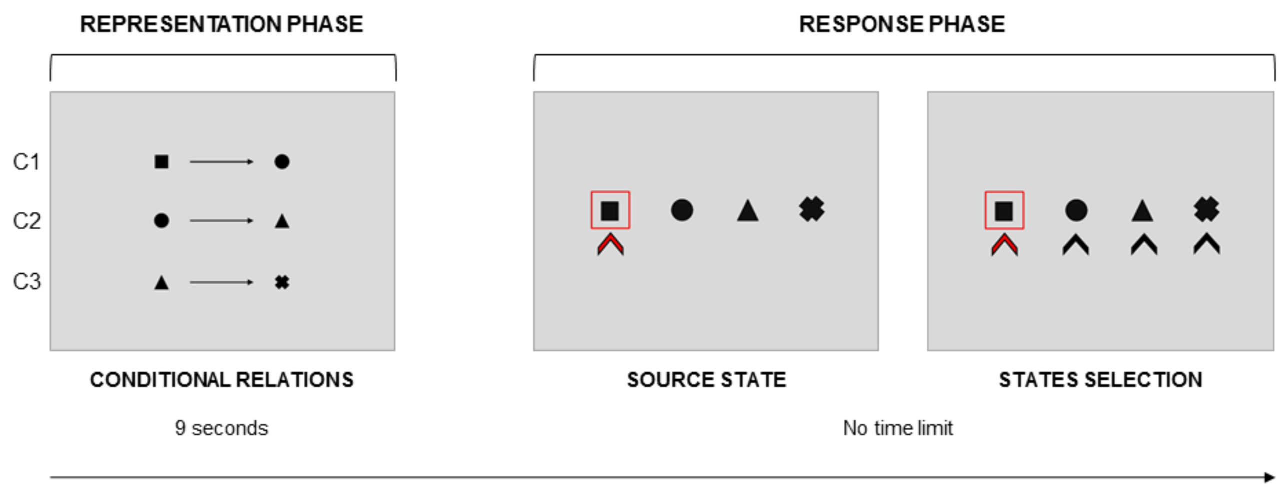

Figure 1.1. Relational-inference task. In the Representation phase (left panel), participants observed for 9 seconds three conditional statements (C1, C2, C3) connecting abstract symbols (states). In the Response phase (right panel), they had to select all the states that necessarily followed the occurrence 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.

[3] 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 S1.1 in section 7.1.1, Appendices).

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 1.2, left panel). In non-linear sets, the underlying relational structure did not match with the order of the presented triplet of conditionals (Figure 1.2, right panel). The presence of inconsistent trials allowed us to disentangle sophisticated from unsophisticated representation processes: sophisticated participants should 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.

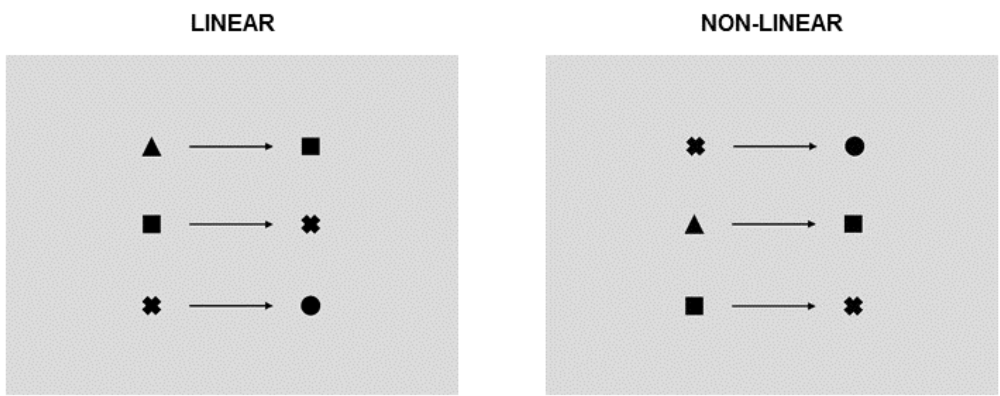

Figure 1.2. Types of symbol configuration in the Relational-inference task. In linear trials (left panel), the spatial order of conditionals (from up to down) matched the underlying relational structure (triangle → square → cross → circle). In non-linear trials (right panel), this was not the case: in fact, the up-down spatial order of conditionals did not match the current relational structure (triangle → square → cross →, circle).

All these aspects were carefully explained to participants with examples, control questions and training trials (we report full instructions and control questions section 7.4.1 in Appendices). In the control questions, participants were asked to make transitive inferences starting from a set of premises and a source state. In case of errors in the control questions, task and transitive properties of conditional inferences were re-explained to participants. After three consecutive errors in the control questions, participants were dismissed. 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 (Figure S1.1 in section 7.1.1, Appendices).

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 7.1.1 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 7.1.1 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 to detect a transitive relation within a relational set. More specifically, we decided to focus on those transitions connecting the consequent of a conditional relation to the antecedent of another conditional, since the compression in a single token of the repeated term allows premise integration in transitive inference (Sternberg, 1980).

We also divided transitive-Ts in linear transitive-Ts and non-linear transitive-Ts (Figure 1.3).

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).

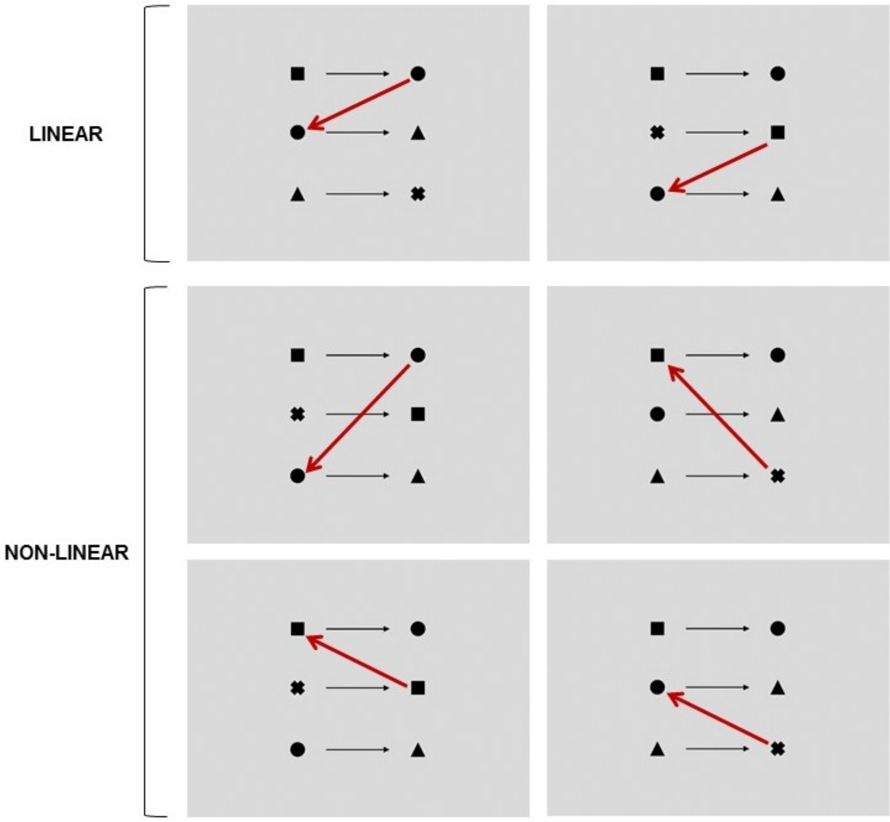

Figure 1.3. Depiction of the six possible transitive-Ts, grouped in linear and non-linear transitive-Ts.

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).*[4] The cluster analysis should return, for each trial, an early cluster (first part of the trial) characterized by shorter fixations and a late cluster (second part of the trial) characterized by longer fixations. 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.[5] 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 1.4). Henceforth, we will refer to these temporal phases as Representation-building and Representation-consolidation intervals. This 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).

[4] 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.

[5] 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).

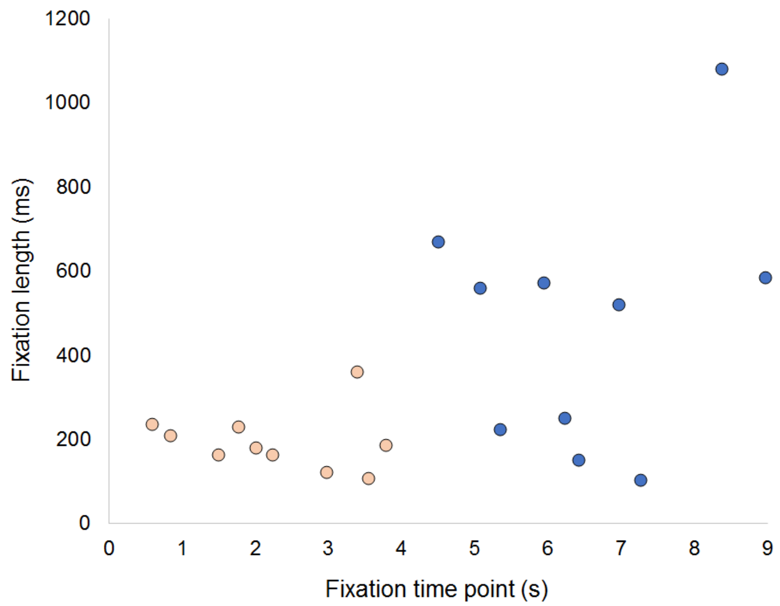

Figure 1.4. Example of cluster analysis on eye-tracking data from one trial of a single participant. Points represent fixations, performed in precise time points within the trial (x axis) and characterized by specific lengths (y axis). Colors of the points express the results of the cluster analysis: an early cluster of short fixations (light orange dots, Representation-building interval) and a later set of longer fixations (blue dots, Representation-consolidation interval).

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). 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).[6] The lower the index value, the lower the distance from the expected distribution of linear and non-linear transitive-Ts.

2.2.2 Hypotheses

Expected gaze patterns in sophisticated and unsophisticated participants

Sophisticated: We expect sophisticated participants to build a representation that explicitly expresses the underlying relational structure of the current relational set. In order to do this, they should search for every possible relation characterizing a specific relational set, showing a high rate of transitions in their Representation-building interval (high Relational Search), exhibiting a homogenous distribution of attention across ROIs, and implementing both linear and non-linear transitive-Ts (low Relational Bias).

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

[6] 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.

of transitions in their representation-building phase (low Relational Search). 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 subset of the six elements (high Attentional Bias). Finally, we do not predict them to perform non-linear transitive-Ts (high Relational Bias), since their strategy requires a simple up-down, left-right sequential and ordered scan path, as expected given western cultural 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. 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.

2.2.3 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 = 0.23). 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 types of process.

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 S1.2 in section 7.1.1 in Appendices), suggesting that the heterogeneity in the three attentional indices was best explained by two types of behavior.

In Figure 1.5, we report results of the cluster analysis ($k = 2$, L1 as distance measures and Relational Search, Attentional Bias and Relational Bias as variables of interest). Cluster-1 (N = 25) was characterized by high Relational Search, low Attentional Bias and low Relational Bias; conversely, cluster-2 (N = 25) showed low Relational Search, high Attentional Bias and high Relational Bias, 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 1.6.

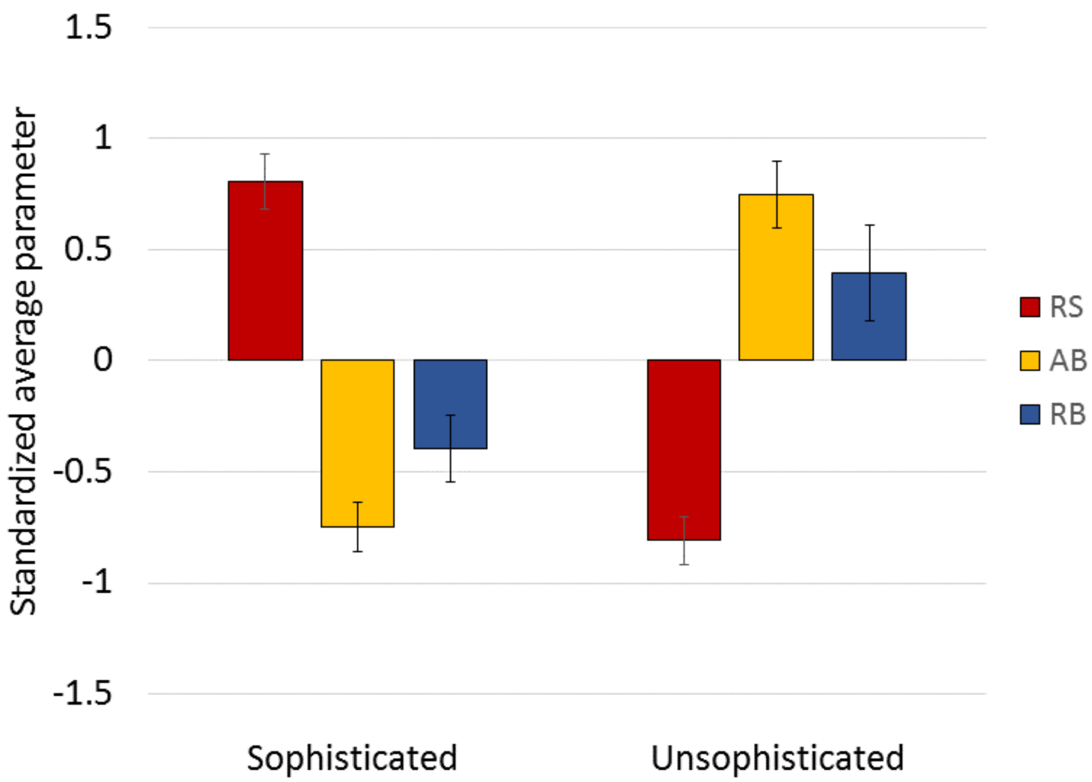

Figure 1.5. Bar graph of standardized indices of visual analysis in the two clusters of participants.

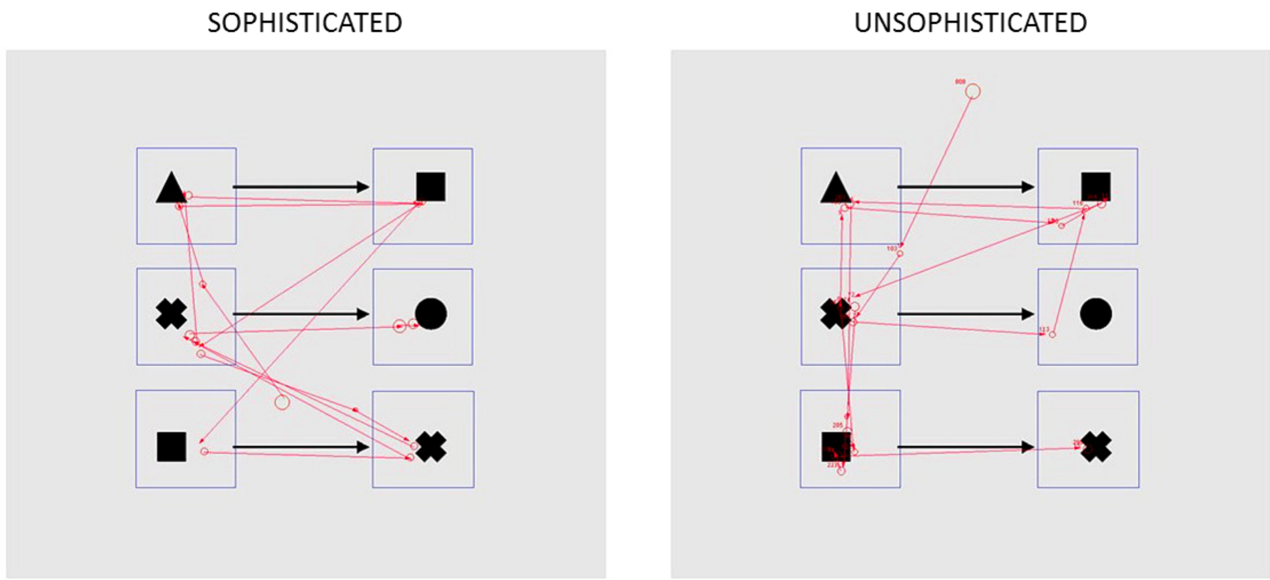

Figure 1.6. Examples of visual analysis of sophisticated and unsophisticated participants in the Representation-building interval. The sophisticated participant (left panel) performed a high number of transitions (red arrows), distributed her fixations rather homogeneously across ROIs (red circles) and 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.

We performed a k-fold cross validation analysis with Lasso estimation (Tibshirani, 1996) to verify that all three attentional parameters were significantly contributing to group clustering. Results indeed confirm that the model that best-explains the group classification is the one containing RS, AB and RB indices (Lasso coefficient: RS = 0.41; AB = -0.42; RB = -0.23).

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 low Relational Search, high Attentional Bias and high Relational Bias 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 S1.8 in section 7.1.1 in Appendices). These results suggest that the inter-group differences observed in the Relational-inference task were not related to general efficiency in scanning the environment.

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 1.7, 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, unsophisticated participants did not show any difference in their proportion of non-linear transitive-Ts across relational sets in fact, they performed a low number of non-linear transitive-Ts along the entire trial in both linear and non-linear trials. This supports the hypothesis that unsophisticated participants were not searching for higher-order relations, and that they did not grasp the relational structure of the current environment.

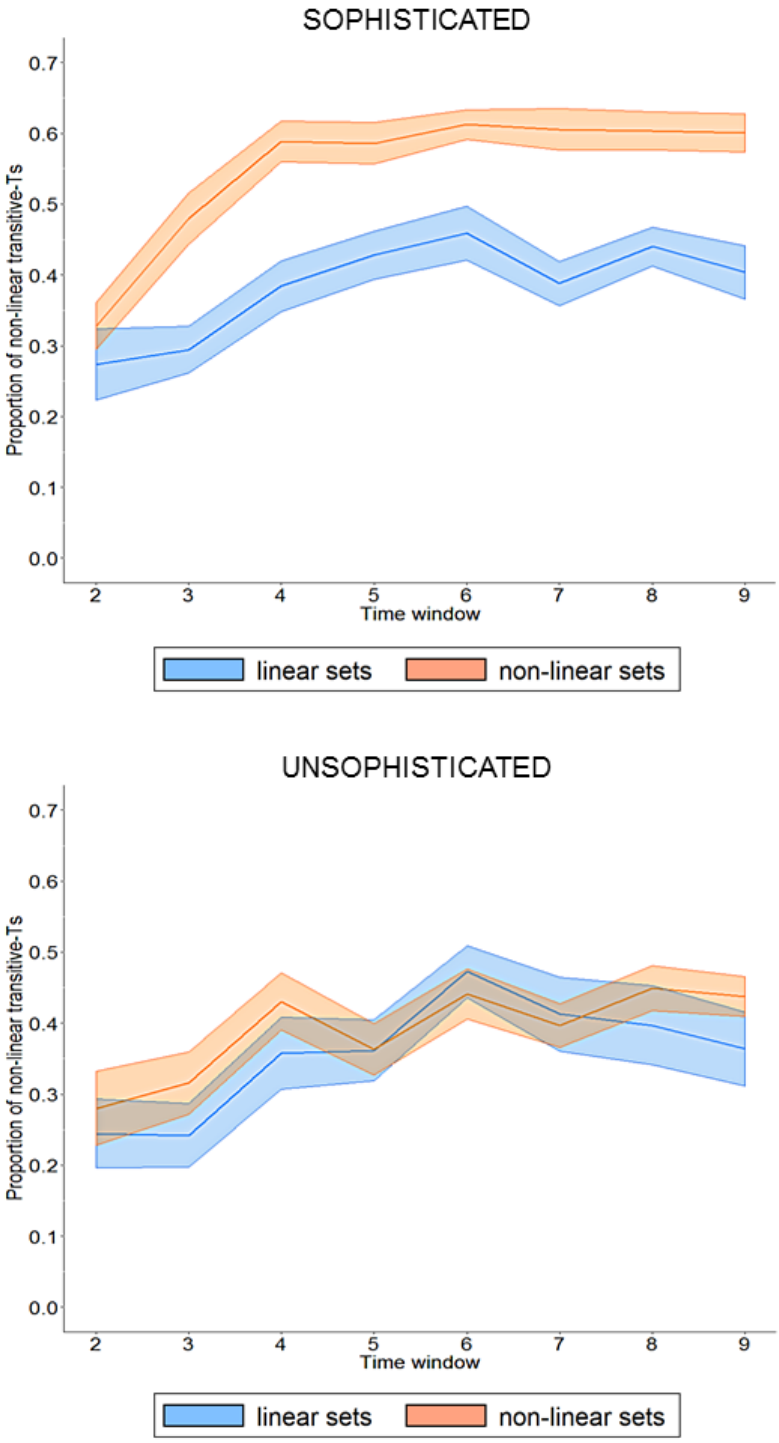

Figure 1.7. Time course of proportion of non-linear transitive-Ts by trial category. We considered time windows of 1 second. The first time window (0-1s) was discarded from the plot because of the extremely low number of transitive-Ts in this time interval (0.004% of the total number of transitive-Ts). Filled areas around lines represent standard error of the mean. Sophisticated participants show a higher proportion of non-linear transitive-Ts in non-linear trials compared to linear trials, while unsophisticated participants do not show any difference between trial categories.

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 1.8 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 optimal than unsophisticated processing, especially when the relational structure underlying the current environment is not explicit and easily recognizable.

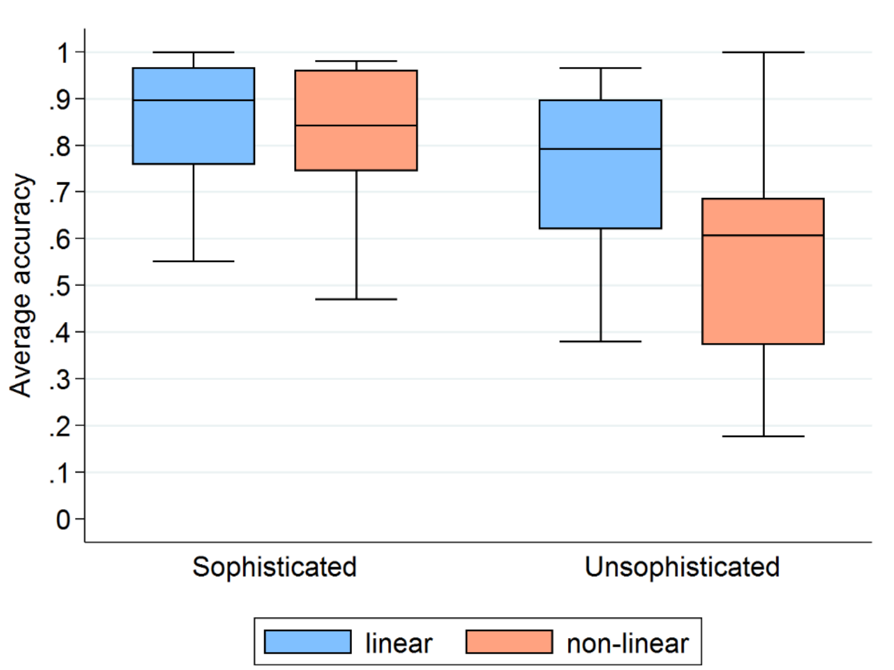

Figure 1.8. Boxplots of mean accuracy for the two groups in the two types of relational set.

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 1.1). 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, $z = 0.26$, $p = 0.397$).

Group	N. obs.	CRT	APM	Forward span	Backward 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 1.1. 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).

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 S1.3 in section 7.1.1 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 S1.4 in section 7.1.1 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 1.2). 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 1.2). These results suggest that fluid intelligence and working memory (in particular, abilities of manipulation of memorized information expressed by the backward digit span, Koenigs et al., 2009) might 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.

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 1.2. 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.

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).[7] Using the

[7] 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.

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 S1.5 in section 7.1.1, Appendices). This finding is in line with the results previously reported (Table 1 in the main text, Table S1.4 in section 7.1.1, 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 S1.6 in section 7.1.1, 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 S1.7 in section 7.1.1, 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 & 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 1.3).

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

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.

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

2.3.1 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.[8] 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 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).

[8] 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.

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 (see section 7.1.2 of the Appendices for detailed instructions provided to participants), independently of the strategy used by the participant in the pre-treatment session. Moreover, participants were informed about the average performance and respective gain of participants using either the sophisticated or the unsophisticated strategy, using data of Experiment 1.[9] After the administration of additional information, participants were told 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 whether unsophisticated participants were prone and able to implement the sophisticated strategy after we ensured that they were aware of its existence and related beneficial effects in terms of performance.

[9] 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.

Eye-tracking analysis

In the pre-treatment session, we replicated the analysis procedure of Experiment 1. We first performed single-trial and single-subject cluster analysis 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, Attentional Bias and Relational Bias. These three indices were used to perform a between-subject cluster analysis to identify sophisticated and unsophisticated participants. Then we 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 based on the behavior observed after the instructions manipulation. Then we performed the same cluster analysis of Session 1 using the new attentional indices, in order to test whether we could observe a change in the proportion of agents implementing the sophisticated or the unsophisticated strategy.

2.3.2 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.

2.3.3 Results and discussion

Session 1: pre-treatment

In session 1 we replicated results of Experiment 1. A cluster analysis of our three attentional indices returned two groups showing the same patterns we had found in Experiment 1. Participants in cluster-1 (N = 36) showed high Relational Search (RS), low Attentional Bias (AB), and low Relational Bias (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, group classification was best-explained by a model including all three attentional indices (k-fold cross-validation, Lasso coefficients: RS = 0.33; AB = 0.38; RB = -0.22).

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 unsophisticated 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, but this did not survive Bonferroni correction ($z = 2.08$, $p = .019$, not significant at Bonferroni corrected threshold $p = .017$ (.05/3))). 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 the representation strategy implemented (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 S1.9 and S1.10 in Section 7.1.2, 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 determined higher levels of accuracy 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 behaviors, 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 observed 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 Relational Search, Attentional Bias and Relational Bias as dependent variables and group (two levels: S-S and U-S groups[10]) as an

[10] The U-U group was not included in any statistical analysis due to the low number of subjects (n = 6). However, comparing descriptive statistics of the three attentional indices pre- and post- manipulation, 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).

We also acknowledge that between-group analyses contained in this paragraph rely on groups with modest sample size, (e.g. the U-S group, N=14) and should be therefore interpreted with caution. However, it must be noted that are confirmatory analyses describing in detail the characteristics and the magnitude of the attentional shift of participants, which has been already revealed by comparing the results of the cluster analyses performed in pre- and post-treatment sessions, and they do not provide novel core findings.

independent factor, F (3, 46) = 5.93, p = .002). These results confirm that a large 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 the sophisticated strategy. 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 independent variable, B = 0.71, p = .043), confirming than the strategy switch led to an increase in performance in the U-S group. However, despite the consistent 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 1.4).

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 1.4. Average performance by group in Pre- and Post-treatment. Standard deviations in

In sum, 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 when we ensure that they are aware of its existence or after repetitive exposure to the task. This suggests that the emergence of unsophisticated behavior is not primarily related to the inability to implement the sophisticated strategy, 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 driver of heterogeneity in Session 1, we would expect similar behavior in Session 2, given that incentives are identical in the two sessions.

Exploring the cognitive drivers of strategy generation

In order to robustly assess the cognitive mechanisms underlying sophisticated and unsophisticated representation strategies, we pooled data of Experiment 1 and Experiment 2 and re-analyzed the role of cognitive factors on a sample of 106 participants. Using this larger sample size, we used cross-validation statistics to investigate 1) the cognitive factors underlying the emergence of either sophisticated or unsophisticated behavior and 2) the cognitive mechanisms modulating task performance in both groups. We considered the CRT score, the APM score and the backward digit span (BDS) as measures of interest since they are the only ones included in both experiments and since they are the only measures significantly modulating strategy generation or performance in Experiment 1.

First, we explored the cognitive factors predicting the classification in sophisticated or unsophisticated groups. Results of a k-fold cross-validation analysis with Lasso estimation (Tibshirani, 1996) confirmed results of Experiment 1 and 2, showing that group classification was best-predicted by a model containing only the CRT as predictor (Lasso coefficient: CRT = 0.31). Figure 1.9 (Panel A) shows average group levels of CRT, APM and BDS in the two groups.

We then analyzed how these cognitive measures modulate intra-group performance in the Relational-inference task (Figure 1.9, Panel B and C). Results of k-fold cross-validation analyses revealed that, in both groups, all three cognitive measures were included in the model that best-explained performance (Lasso coefficients. Sophisticated: CRT = 0.12; APM = 0.47; BDS = 0.25. Unsophisticated: CRT = 0.16; APM = 0.46; BDS = 0.37). These results corroborate the findings of Experiment 1 and Experiment 2, showing a crucial involvement of fluid intelligence and working memory in sustaining performance in the task, but not in predicting the emergence of either sophisticated or unsophisticated representation behavior.

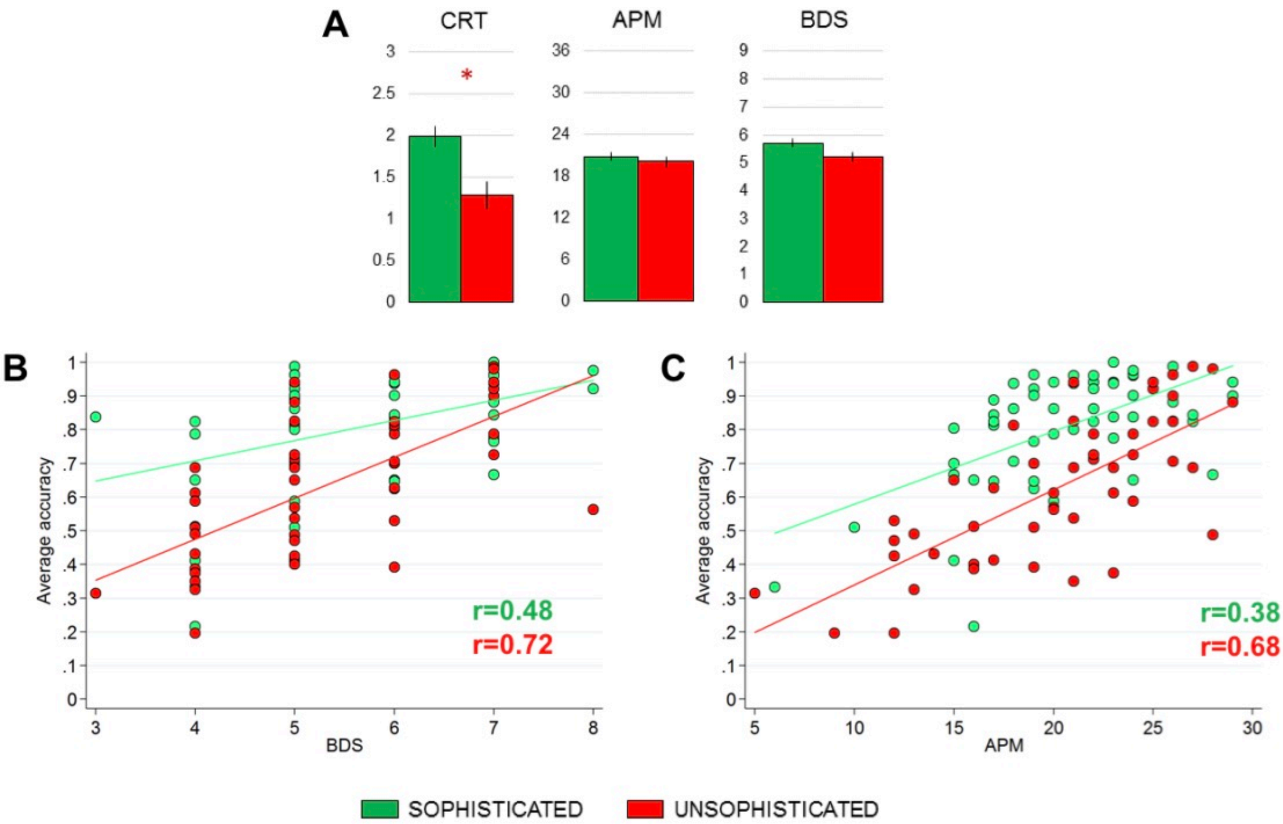

Figure 1.9. Visualization of cognitive measure analyses in Sophisticated (green) and Unsophisticated (red) groups. A) Average levels of CRT, APM and BDS in the two groups. B) Scatter plot of BDS and average accuracy in the Relational-inference task. Correlation coefficients r for both groups are reported. C) Scatter plot of APM and average accuracy in the Relational-inference task. Correlation coefficients r for both groups are reported.

2.4 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.

2.4.1 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. The task was incentivized similarly to the previous experiments, by paying participants 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 1.5). 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).

	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 1.5. Examples of items in the Verbal Conditional Sequence task

Conditional sequences could contain different types of inference. We used several inference types since we hypothesized that the nature of the relationship between antecedent and consequent could influence the relationship between representation strategy and validity judgment in the task. Types of inference consisted in modus ponens (MP), modus tollens (MT), affirmation of the consequent (AC), denial of the antecedent (DA). Some conditional sequences consisted in two inferences of the same type (e.g. MP ∴ MP), while other sequences consisted in two different inference types (MP&DA; MT&AC).[11]

[11] 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.

In sum, sequences differed between 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, DA, MP&DA; MT&AC).

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 bound the conditional statements (i.e. constructing a model of the premises) before knowing anything about the actual occurrence of states (as in the Representation Phase of the Relational-inference task).[12] 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 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 1.10). 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).

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.

[12] In the Verbal-inference Task, the distinction between representation-building and representation-consolidation stages is meaningless, since participants have all the pieces of information available until their decision.

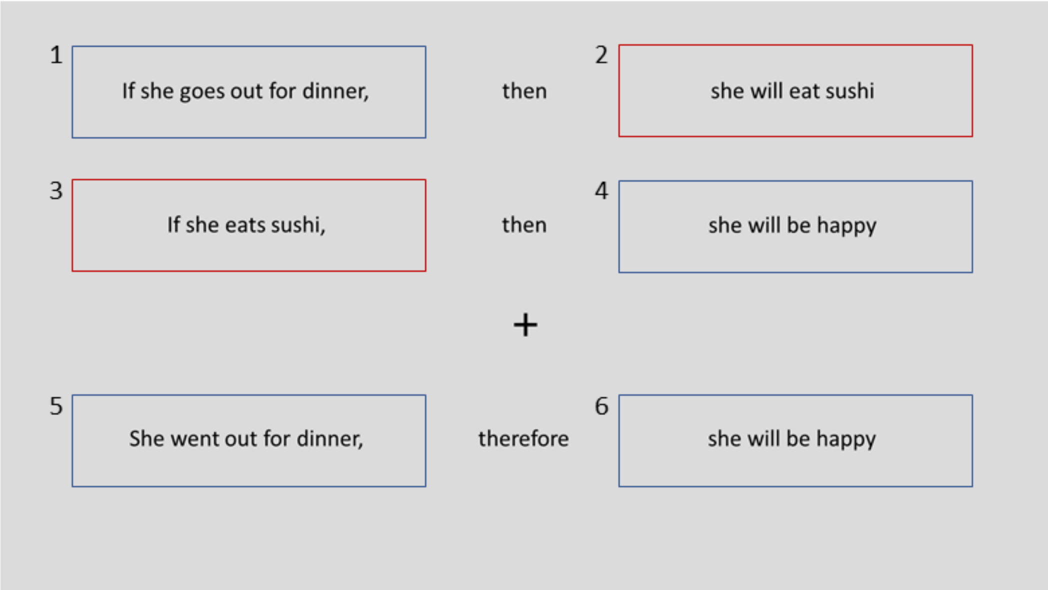

Figure 1.10. Example of trial with ROIs (not shown to the participants) used for eye-tracking analysis. R1-R4 constitute the premises of the argument, and fixation falling in these ROIS before any fixation occur in R5-R6 are included in the Representation-building phase. In this example, ROIs in red represent the shared proposition.

Using data from this interval, we investigated whether sophisticated participants tended to focus more on the integration of the two conditional statements in order to form an exhaustive and explicit model of the relational structures underlying the premises. Specifically, we focused on transitions connecting the two states of the shared proposition following the temporal order of events (i.e. independently of the spatial order of conditionals). 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). We mainly focused on the proportion of *non-linear* integrative-Ts in *non-linear* sets since they were the most informative in reflecting processes of premise integration. In fact, in linear trials, the presence of a linear relation between conditionals does exclude the presence of non-linear relations between premises.

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 1.11).

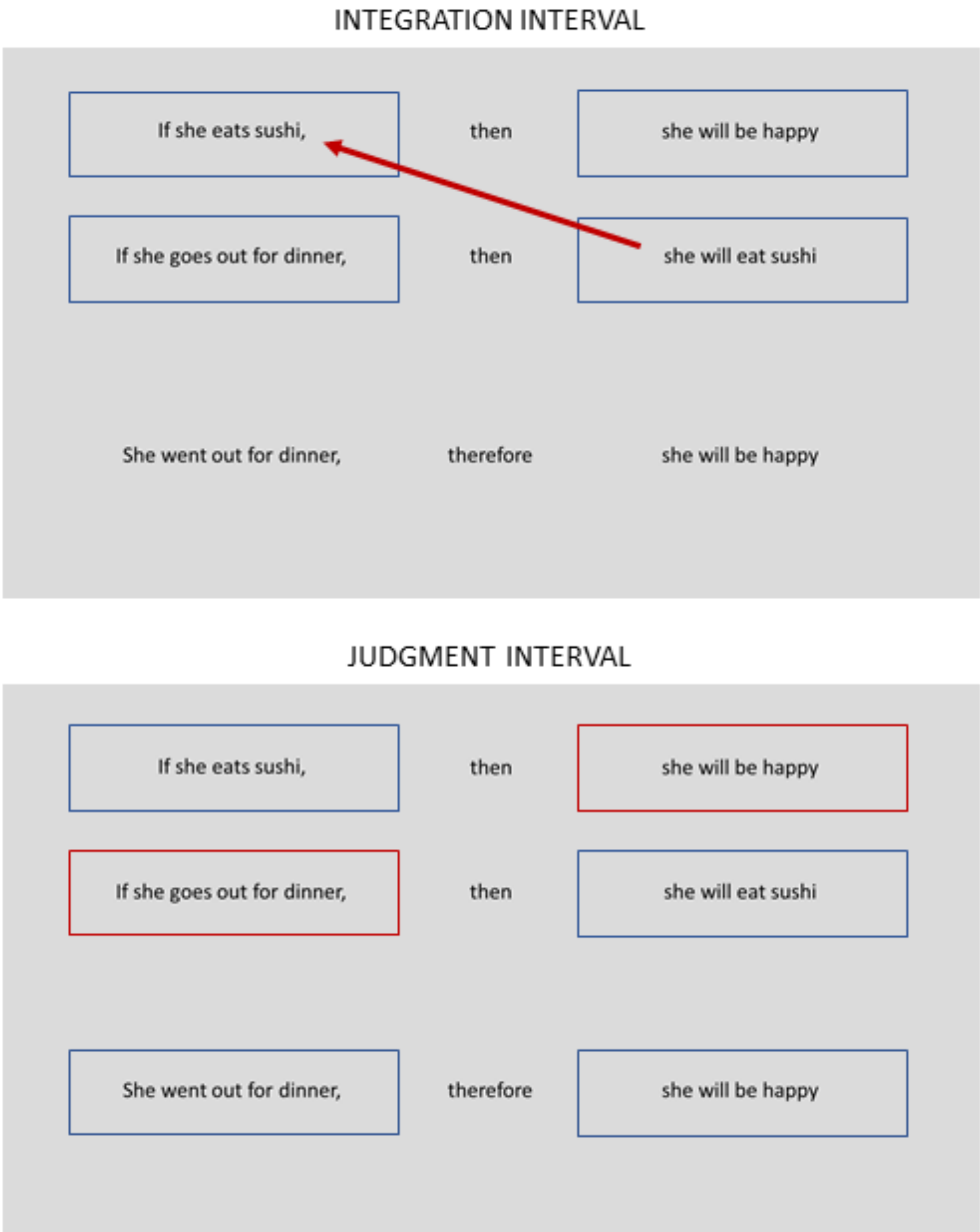

Figure 1.11. Key transitions and ROIs for eye-tracking analysis in the Verbal-inference task. In the Integration interval (upper panel), when participants did not acquire any information about the occurrence of states and inference to evaluate, we analyzed the proportion of non-linear integrative-Ts (red arrow) in non-linear relational set.

In the judgment interval, after that participants looked at the assertion or the conclusion), we focused on distribution of attention and depth of information processing in the Judgment states (red ROIs) in comparison to the other four ROIs (in blue).

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.

2.4.2 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 without having built a comprehensive representation of the relationship underlying hypothetical states in 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 attentional indices indicating a more pronounced process of integration and evaluation of relations between hypothetical states to modulate the ability to judge the validity of conditional arguments, since they reflect a deeper understanding of the underlying relational structure. More specifically, we hypothesize that unsophisticated processes of encoding and integration of relational structures affect the ability to judge the validity of inferences whose relationship among contingencies is not trivial (e.g. AC and DA). More specifically, in these types of structure, processing in a superficial way the relationship between antecedent and consequent (i.e. devoting relatively less attention on the Judgment states in the Judgment interval) may lead to a misrepresentation of the inferential relationship between contingencies, leading to inferential fallacies.

2.4.3 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) affected 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 1.6 reports average performance for each type of inference (MP, AC, DA, MT, MP & DA, MT & AC).

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

Table 1.6. 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.

Representation behavior in the Verbal-inference task

In the Integration interval, we tested whether sophisticated agents (following participants' classification in the Relational-inference task) tended to integrate premises in a unitary model of the relational environment to a greater extent than unsophisticated ones. 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 were integrating the two conditional statements in a relationally explicit model before moving to the assertion. In order to describe this effect, in Figure 1.12 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 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 of the environment and focused on the integration of the two conditional statements to build a comprehensive model of the hypothetical scenario.

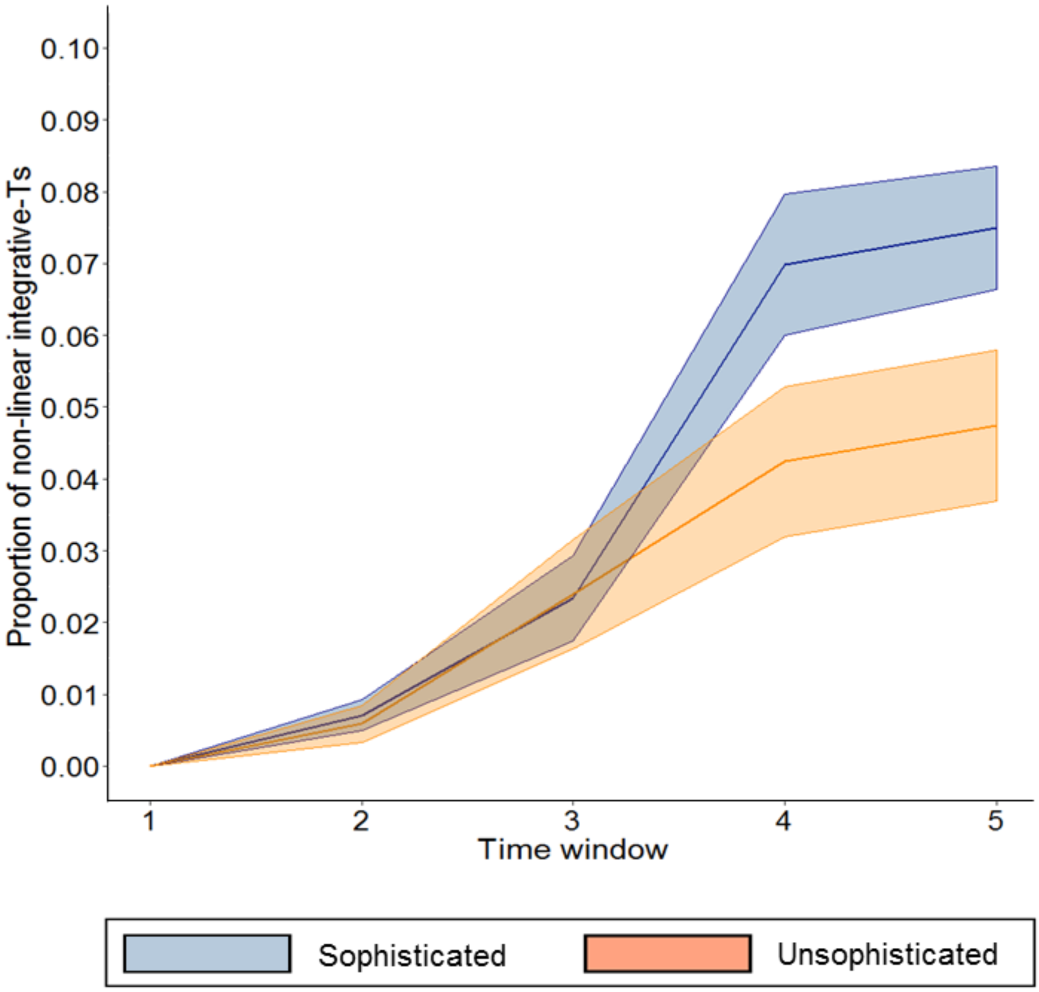

Figure 1.12. Time course of proportion of non-linear transitive-Ts (over the total number of between-ROI) transitions by group in the Integration interval of non-linear trials. Fixation distribution was normalized across trial time by assigning fixations to five homogeneous intervals based on total number 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.

Afterwards, we compared attentional indices in the Judgment interval across groups. Results show that sophisticated agents, when compared to unsophisticated ones, spent a higher proportion of 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, $p = .021$). Interestingly, the attentional index in the Integration interval predicted the level of indices in the Judgment interval (Table 1.7), suggesting that the tendency to integrate premises in a unitary relational model during integration was associated with the tendency to focus on key pieces of information during the validity judgment.

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

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 S1.11 in section 7.1.3, 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 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, in order to explore its effect on performance. We ran a multivariate regression with the six inference categories as the dependent variables and proportion of time spent in the Judgment states as independent variable, and we found that the attentional index predicted higher performance in AC, DA, MT&AC and MP&DA inference categories (Table 1.8).

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

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 dependent variable and APM score, CRT score and backward digit span as independent factors. Result indicated that working memory, as reflected by the backward span, predicted performance in the task ($B = 0.38$, $p = .005$),[13]

[13] Working memory had a significant impact on MP ($B=0.34$, $p=.010$) and DA ($B=0.35$, $p=.011$) inferences, a marginally significant effect on MT&AC ($B=0.24$, $p=.076$) and AC ($B=0.26$, $p=.053$) inferences and no effect on MP&DA ($B=0.22$, $p=.102$) and MT ($B=-0.12$, $p=.395$) trials (Table S1.12 in section 7.1.3, Appendices).

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).

In sum, 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 a general, context-independent heterogeneity in the way agents build relational representations of contingencies.

2.5 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 between 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 among 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 did predict 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. Individual CRT levels may indeed capture the agents' propensity to instantiate more or less deliberative and thoughtful processing, which modulates the probability of a specific agent to generate a more or less sophisticated representation strategy in a given environment. This propensity may be linked to inter-individual differences in the cognitive cost of associated with the implementation of more or less deliberative processing, or to meta-cognitive factors modulating the evaluation of the effectiveness of potential strategies in absence of feedback and exogenous cues. This hypothesis indeed suggests that the presence of informative cues about the existence of alternative (better) strategies could lead to the re-evaluation of the current unsophisticated strategy in favor to more sophisticated ones.

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.

3. Study 2: Disclosing the link between cognitive reflection and sophistication in strategic interaction: the crucial role of game representation.

3.1 Introduction

In our everyday experience, we often face situations in which the outcomes of our decisions are influenced by the decisions of other agents. Traditional game theory uses the concept of Nash equilibrium to describe and predict normative behavior of players who are assumed to be fully rational and have perfect beliefs about other players' actions. However, extensive experimental evidence has been showing that agents' choices often depart from Nash equilibrium strategies (Grosskopf & Nagel, 2008). In order to explain the heterogeneity observed in interactive games, behavioral models of strategic thinking such as Level-K (Crawford, 2003; Crawford et al., 2013; Nagel, 1995; Stahl & Wilson, 1995) and Cognitive Hierarchy (CH, Camerer et al, 2004; Chong et al., 2016; Ho et al., 1998) modelled players' behavior in terms of hierarchical levels of strategic thinking (Nagel, 1995) by relaxing the rationality assumptions implied in equilibrium theories. These models describe the strategy space of players building a hierarchical structure that predicts, at the bottom, players who play randomly (level-0). The second step in the hierarchy corresponds to level-1 players, who best respond to the belief than the counterparts are level-0; the following step predicts level-2 players, who best respond to the belief that the opponents are level-1 (in Level-k theory) or a mixture between level-0 and level-1 (in Cognitive Hierarchy theory), and so on, increasing the number of steps of strategic thinking. In other words, behavioral models of strategic thinking assume that each player has to estimate the level of rationality of the other agents involved in the interaction (Pantelis & Kennedy, 2017). However, it is not clear if players applying few steps of strategic thinking do so because they believe that the other players are bounded rational, or because they are bounded rational themselves (Goodie et al., 2012; Grosskopf and Nagel 2008). In this regard, one of the crucial components of mentalizing concerns the constructions of an exhaustive and correct mental model of the decision space of the counterpart, in order to predict her next action and therefore best-respond to it (Hedden & Zhang, 2002). However, accumulating experimental evidence suggests that deviations from normative responses in strategic interaction depend on poor game representations. These misrepresentations may arise from the generation of a miserly model of the opponent's incentives and potential moves (Verbrugge et al., 2018), the relational structure of the game payoffs (Devetag & Warglien, 2008) or the relationships between own and other's potential actions and outcomes (Rydval et al., 2009).

Gaze patterns and game representation

Given the importance of mechanisms of information encoding and representation in strategic interaction, in the last years accumulating process-tracing research has explored processes of game (mis)representation by observing the patterns of information acquisition characterizing game playing. Costa-Gomes et al. (2001) used mouse-tracking to disclose the process of information search in normal form games, identifying nine strategic types of player. A relevant proportion of these participants exhibited choices and information acquisition patterns consistent with predictions of level-k models. Hristova & Grinberg (2005) showed that cooperative behavior in a Prisoner Dilemma (PD) game was linked to the distribution of attention between payoffs matrix and opponent's moves. In two mouse-tracking experiments, Brocas et al. (2014, 2018) showed that failure in looking at the required pieces of information predicts out-of-equilibrium play in private information games (Brocas et al., 2014) and sequential and simultaneous dominance solvable games of complete information (Brocas et al., 2018). Polonio et al. (2015) used eye-tracking to cluster participants in types of player depending on their frequency distribution of classes of transitions connecting matrix payoffs. The cluster analysis returned three categories of player: 1) players focusing on their own payoffs, 2) players mostly performing intra-cell comparisons, and 3) players with distributed attention. The two former types did not perform the payoff comparisons necessary for individuating the equilibrium strategy. In particular, players focusing on own payoffs did not incorporate the possible actions of the opponent in their decision model and chose in accordance to the expected strategy of a Level-1 (L1) player, who responds to the belief that the opponent does not have a preferred action. Players that focused on intra-cell comparisons did considered opponents' payoffs, but framed the problem as a pure coordination game, disregarding dominant choices of the opponent. In contrast, both visual analysis and choices of the latter type of player were consistent with the expected behavior of a Level-2 (L2) player, who assumes that the counterpart is a L1 player and, given such belief, best responds to the expected counterpart's action.[14]

Altogether, these results suggest that some players systematically misrepresent and simplify interactive problems. Importantly, game misrepresentation leads to deviation from game theoretical equilibrium choices, supporting the idea that the internal representation of the game structure is a crucial component of the interactive decision process.

Game representation, cognitive reflection and strategic sophistication

In recent years, extensive experimental research has sought to investigate whether specific cognitive factors could explain individual differences in strategic sophistication. Several studies have indeed shown correlations between behavior in games and different measures of cognitive ability and executive functions (Burks et al., 2009; Burnham et al., 2009; Gill & Prowse, 2016). Among these measures, the Cognitive Reflection Test (CRT, Frederick, 2005) has been the most successful in explaining choices in several interactive games, including the Beauty Contest Game (Carpenter et al., 2013; Fehr & Huck 2016; Garza et al., 2009), the Hit 15 game (Carpenter et al., 2013), bunk-run

[14] Concerning the relationship between Level-k models and gaze data, see also Stewart et al. (2016) who showed inconsistencies between patterns of information acquisition and Level-k or Cognitive Hierarchy models.

games (Kiss et al., 2016) and matrix games (Georganas et al., 2015; Hanaki et al. 2016). The CRT traditionally assesses the individual tendency to implement one of two types of cognitive process: those that are slower and more reflective and those executed rapidly with little conscious deliberation. In particular, a high cognitive reflection level reflects the ability to reason exhaustively about the characteristics of a problem, inhibiting intuitive but incorrect responses. Nonetheless, in recent years, several studies suggested that the CRT assesses the implementation of different cognitive styles, rather than a reflective suppression of an initial response (Baron et al., 2014; Mata et al., 2013; Szaszi et al., 2017). In particular, high cognitive reflection levels have been linked to the tendency to use more thorough search processes (Cokely & 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). Moreover, 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). Conversely, a low cognitive reflection level is associated with miserly information processing (Toplak et al., 2014). Taken together, these findings indicate a crucial involvement of cognitive reflection in processes of information encoding, integration and representation. In the context of strategic interaction, we therefore believe that cognitive reflection may specifically modulate game representation mechanisms, which in turn predict the level of sophistication in strategic interaction.

To test this hypothesis, we conducted two eye-tracking experiments involving one-shot games. In Experiment 1 participants played 2x2 matrix games, while in Experiment 2 we increased matrix complexity introducing 3x3 matrices. Experiment 2 was designed to explore the generalizability of the effect of cognitive reflection on game play, and investigate whether game complexity could have an impact in the hypothesized relationship between cognitive reflection and game representation. We analyzed participants' gaze patterns to reveal the type of game representation that they were building, and administered the Cognitive Reflection Test (CRT) to obtain individual measures of cognitive reflection. Additional measures of fluid intelligence and working memory abilities were collected to control for the specificity of the effect of cognitive reflection. Both experiments are based on the same analysis structure. First, we tested whether cognitive reflection predicts strategic choices and hierarchical levels of strategic thinking in games. Second, we explored the relationship between game representation and strategic behavior by individuating patterns of information acquisition that could predict the level of sophistication in strategic choices. Third, we explored the relationship between patterns of information acquisition and cognitive reflection. Finally, we tested whether gaze patterns mediate the relationship between cognitive reflection and choices.

3.2 Experiment 1

3.2.1 Methods

Participants and procedure

Participants were 48 students from the University of Trento, Italy (34 females, mean age 23.02, SD 2.84). The study was approved by the local ethics committee and all participants gave informed consent. Participants performed thirty-two 2x2 one-shot matrix games. Before playing the games, they were instructed on the procedure and were provided with examples and training trials (4 games). Moreover, we administered control questions to participants to verify that they have fully understood task and procedure of payment. If participants failed to answer control questions, instructions were repeated (detailed instructions and control questionnaires are reported in section 7.4.2 of the Appendices). All participants played in the role of row player[15] and were instructed to choose between row I and row II by key-press. The order of games was randomized across participants. Each game

[15] In order to pair each participant with an opponent, the 32 games consisted of 16 pairs of isomorphic games in which row and column payoffs were identical but switched; in such a way, it was possible to match the choices of two row players as they have played in two different roles.

was played only once and no feedback was provided at the end of games. Trials were preceded by a fixation-point positioned in one of four possible locations outside the matrix. At the end of the experimental session, three games were randomly selected and the player's choice in each game was paired with the choice of another player in that very same game. Participants received the sum of the outcomes of the three games in euros (from 3 to 27 euros).

In addition to 2x2 games, all participants performed the Cognitive Reflection Test (CRT, Frederick, 2005). Moreover, we administered some control measures of cognitive ability to participants, in order to control for the specificity of the hypothesized relationship between cognitive reflection and strategic sophistication. To control for fluid intelligence, participants completed the Raven Advanced Progressive Matrices Test (APM; Raven et al., 1998). We also collected several measures of working memory, including digit span forward and backward (Wechsler, 2008) and the n-back task (Kirchner et al., 1958). Forward digit span measures abilities in simple short-term maintenance and recall of digits, while the backward span requires an additional component of mental manipulation of elements (Baddeley, 1996; Monaco et al., 2013). The n-back task assess the ability to actively maintain and update information in working memory, and targets mechanisms linked to executive control such as inhibition and interference resolution (Kane, Conway, Miura, & Colflesh, 2007). We report the exact procedure of these control cognitive tests in section 7.2.1 of the Appendices.

2x2 Matrix games

We used two classes of games characterized by different equilibrium structures, creating sixteen 2x2 games for each class (for a full list of game matrices, see Figure S2.1 in section 7.2.1, Appendices). The two classes of games (Figure 2.1) were: (1) dominance solvable "self" games (DSS), in which only the participant had a strictly dominant strategy; (2) dominance solvable "other" games (DSO), in which only the opponent had a strictly dominant strategy.[16] Both dominance-solvable games had a unique pure strategy Nash equilibrium. DSO games differ from DSS games because they need two steps of iterated elimination of dominant strategies that include the evaluation of the counterpart's incentives (first, individuating the strict dominance of the counterpart; second, choosing the best response given the opponent's dominant choice). In contrast, DSS games need only one step of iterated elimination of dominant strategies between participant's own possible choices. Therefore, only the DSO games require strategic sophistication to individuate the equilibrium strategy. Games within a class could vary in terms of magnitude of payoffs and location of the payoffs in the matrix, but maintained the described relations of dominance between choices.

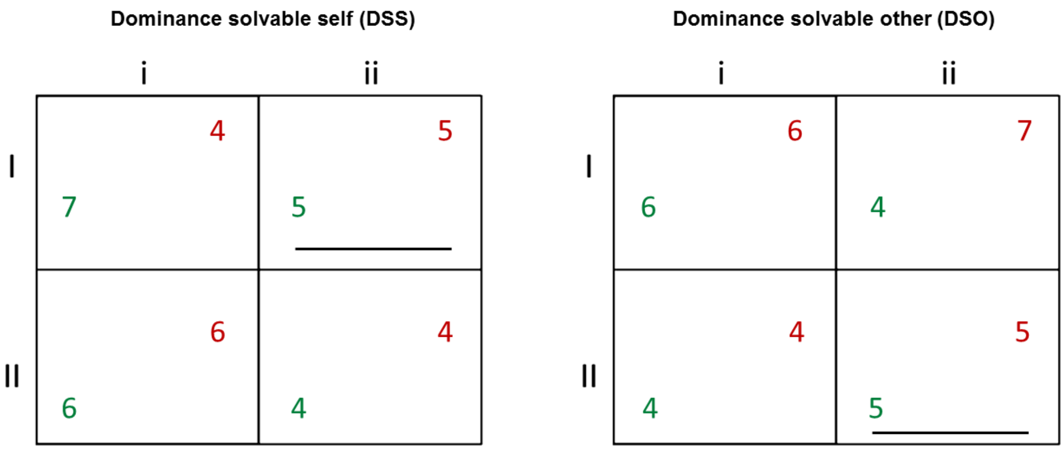

Figure 2.1. Examples of dominance solvable self (DSS) and dominance solvable other (DSO) games. All participants played in the role of row players. In this example, we report two isomorphic games in which row and column payoffs are identical but switched. The line in one of the cells of each matrix signals the equilibrium solution of the game.

[16] The presence of a dominant strategy for a player implies that one strategy is better than the alternatives independently on the opponent's move (Fudenberg, Tirole, 1991).

Eye-tracking procedure

While playing matrix games, 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 1080 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.

In matrix games, we used a calibration with 13 points: points were placed in the exact locations of payoffs, at the center of the matrix and in the four possible locations of the fixation cross. After the calibration phase, a validation phase was performed to make sure that the calibration was accurate. The position of points 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. Before the beginning of each trial, a drift correction was performed in order to control that participants look at the current fixation location; stimuli were presented after the fixation point was fixated for 300 milliseconds. Stimuli were placed at an optimal distance between each other in order to precisely distinguish goal-directed saccades and fixations.

Gaze data analysis

Following the eye-tracking analysis performed by Polonio and colleagues (2015), we defined eight regions of interest (ROIs), centered on the matrix payoffs. All the ROIs had a circular shape with a size of 36000 pixels. The ROIs covered only 23% of the game matrix area and did not overlap. All the fixations that did not fall within any ROIs were discarded. However, although a consistent portion of the matrix was not included in any of the ROIs, the large majority of fixations (87.4%) were located inside the ROIs.

Both fixations[17] and saccades were taken into consideration for eye-tracking data analysis. More specifically, we focused on two main types of variable: fixation location and type of transition. Fixation location was useful to explore, for each player, the distribution of attention between own and other's payoffs, revealing if players incorporate others' incentives in their model of the interactive problem. Transitions expressed eye movements from one payoff (AOI) to the next, and provided information about the exact types of information that participants were processing. In particular, we considered those transitions that were useful to extract information about the structure of the payoff matrix and build a representation of the current interactive problem. In order to explore the type of visual analysis performed by participants, transitions were divided in five major types (Figure 2.2), following the classification of Devetag and colleagues (2016):

1) own-payoffs within-action transitions: transitions between player's own payoffs within a single row (necessary to identify the action with the highest average payoff).

2) own-payoffs between-action transitions: transitions between player's own payoffs within a single column (necessary to identify the presence of own dominant choices).

3) other-payoffs within-action transitions: transitions between the counterpart's payoffs within a single column (necessary to identify the counterpart's choice with the highest average payoff).

4) other-payoffs between-action transitions: transitions between the counterpart's payoffs within a single row (necessary to identify the presence of counterpart's dominant choices).

5) intra-cell transitions: transitions between the payoffs of the two players, within the same cell (necessary to compare the two players' payoffs given a specific combination of choices).

[17] A fixation was defined as an interval in which gaze was focused within 1° of visual angle for at least 100 ms (Manor and Gordon, 2003).

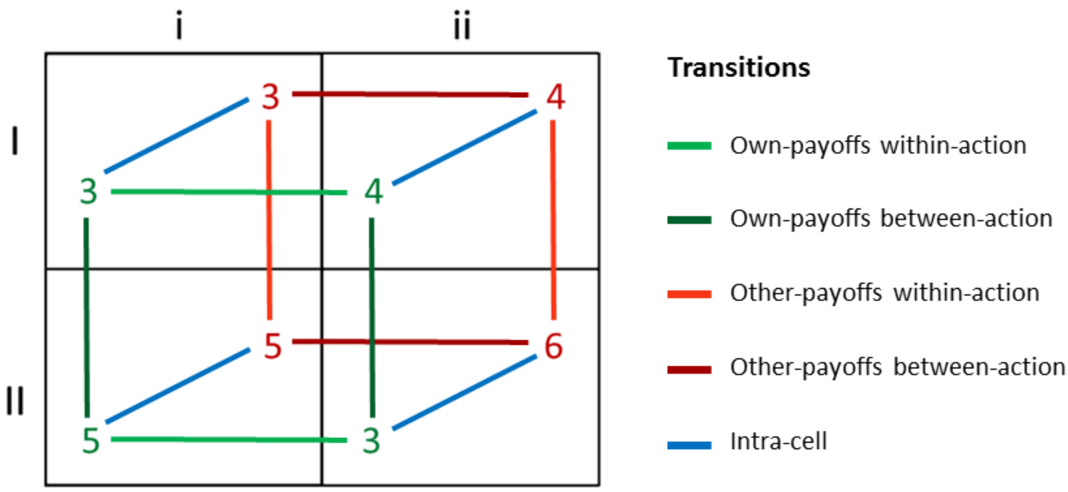

Figure 2.2. Types of relevant transitions between payoffs. The direction of the transition from one payoff to the other is irrelevant for classification.

Each type of transition expresses the encoding of specific pieces of information within the payoff matrix. Exploring individual patterns of information acquisition, we can understand how players are representing the current interactive problem, and therefore predict which model of choice they will implement.[18]

3.2.2 Hypotheses

In Experiment 1, we predict that cognitive reflection modulates processes of game representation, as expressed by gaze patterns, and individual levels of strategic sophistication in 2x2 games.

Behaviorally, we expect high CRT players to show higher levels of strategic thinking in the framework of the Cognitive Hierarchy model. High CRT players should therefore play more often

[18] Other types of transitions that are excluded from this classification (e.g. transitions connecting own and other's payoffs across cells) do not allow to extract relevant information about the payoff structure, as already shown in previous works (see for instance Devetag et al., 2016).

the equilibrium strategy in DSO games, since in these games they have to make predictions about the possible actions of the counterpart and respond to such beliefs in order to play equilibrium.

At the same time, we expect the CRT score to predict sophistication in the visual analysis of the game matrix. Specifically, we hypothesize high CRT players to exhibit the typical gaze patterns of more sophisticated types of players (Costa-Gomes et al., 2001; Devetag et al., 2016; Polonio et al., 2015; Polonio & Coricelli, 2018). High CRT players should exhibit a higher proportion of other-payoff within-action transitions, suggesting the attempt to form precise (non-diffuse) beliefs about the action of the counterpart, and to individuate the counterpart's action with the highest average payoff, which is the expected action of a less sophisticated level-1 counterpart (Bhatt & Camerer, 2005; Costa-Gomes et al., 2001). On the contrary, we expect low CRT players to rely on a less exhaustive game representation that does not incorporate other's incentives, and therefore to show an attentional bias for players' own payoffs. Specifically, we predict low CRT players to exhibit a higher rate of own-payoffs within-action transitions and a low proportion of other-payoffs within-action transitions, consistently with the level-1 strategy. Moreover, high CRT players should show the typical temporal pattern of information acquisition observed in sophisticated players (Polonio et al., 2015). This pattern should consist of 1) a first evaluation of own payoffs, to detect potential dominant strategies, 2) a subsequent exploration of other's incentives to form beliefs about the expected action of the other player, and 3) a final re-observation of own payoffs to best respond to the expected action of the counterpart.

Finally, we hypothesize that the relationship between CRT score and strategic choices is mediated by the level of sophistication of the visual analysis of the payoff matrix.

3.2.3 Results

Behavioral results

The proportion of equilibrium responses in DSS games was high in the majority of our participants (M = 0.85, SD = 0.17). Conversely, the distribution of equilibrium responses in DSO games was much more heterogeneous, and the proportion of equilibrium responses in these games was significantly lower than in DSS games (M = 0.56, SD = 0.22, Wilcoxon matched-pairs signed-rank test, z = 5.21, effect size (r) = 0.75, p < .001). These results confirm that heterogeneity in strategic sophistication emerges in those games in which taking into account the possible incentives of others is fundamental.

Cognitive reflection and strategic sophistication

In order to investigate the specific relationship between cognitive reflection and strategic choices, we ran a stepwise backward regression to test the effect of the CRT score on the average proportion of equilibrium responses in DSO games, controlling for Raven score and the three measures of working memory (Table 2.1). Result indicate that the CRT score (B = 0.33, p = .022, $F(1, 46) = 5.59$, $R^2 = .11$) was the only cognitive measure significantly predicting sophistication of choices, while we did not find any effect of fluid intelligence or working memory on strategic behavior (Table 2.1). These results highlight the crucial role of cognitive reflection in strategic thinking.

Proportion of equilibrium responses	B	SE	t	p	95 % CI	
CRT score	0.33	0.14	2.36	.022	0.05	0.61
N. obs.	48					

Table 2.1. Stepwise backward regression of proportion of equilibrium response in DSO games, with CRT score, Raven score, forward digit span, backward digit span and N-back score as independent variables. Only cognitive measures surviving the limit for inclusion in the model (p < .05) are reported in the table. Variables excluded from the model: Raven score, p=.49; digit span forward, p=.28; digit span backward, p=.20; n-back score, p=.37.

To corroborate this finding, we ran a k-fold cross-validation analysis (Lasso estimation) using all cognitive measures as factors and the proportion of equilibrium responses in DSO games as dependent variable. Cross-validation results confirm the ones of stepwise backward regression, showing that the best cognitive model in explaining the variability in equilibrium responses includes only the CRT score as predictor (Lasso coefficient, CRT = 0.04). In Figure 2.3 we report visualization of the relationship between our five cognitive measures and the proportion of equilibrium responses in DSO games.

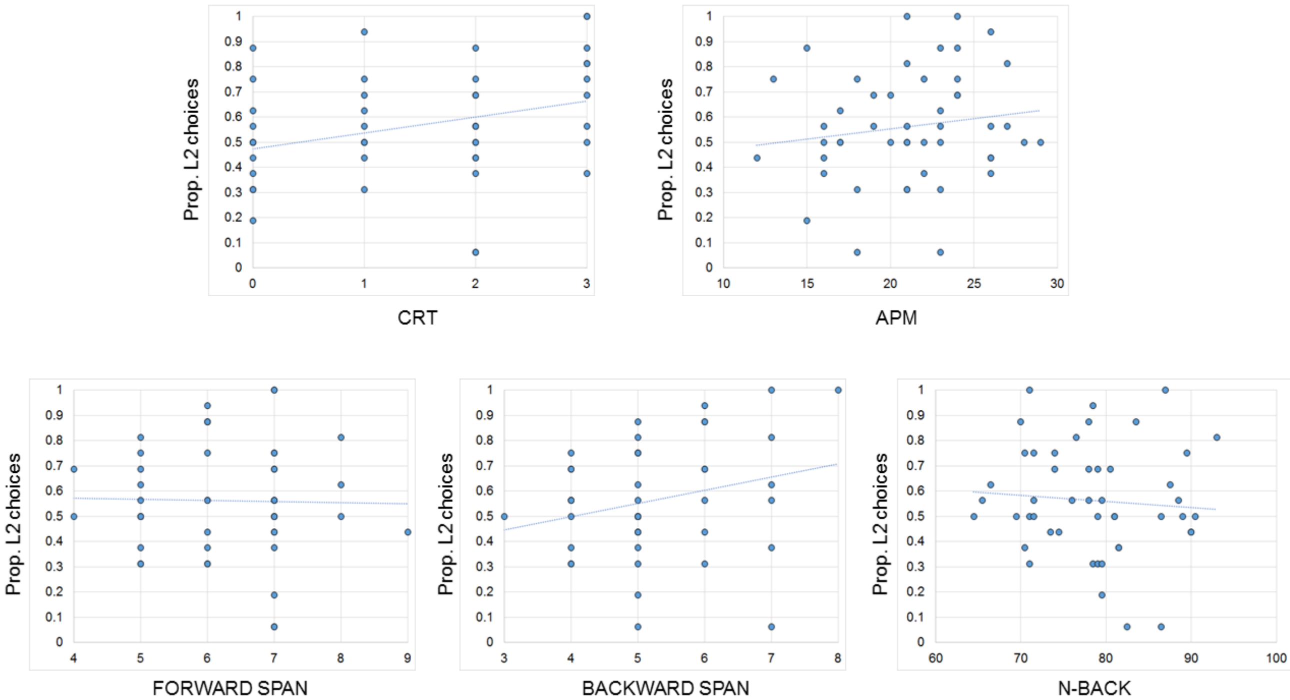

Figure 2.3. Scatter plots of the five cognitive measures and the proportion of equilibrium (L2) responses in DSO games.

Then we run another regression to analyze the specific effect of cognitive reflection levels on strategic choices, treating CRT as a group factor (Table 2.2). The model accounted for 20 % of the variance of choices ($F(3, 44) = 3.64$, $p = .020$, $R^2 = .20$). The effect was indeed driven by a specific level of the cognitive reflection factor (CRT = 3, B = 1.17, p = .004), which was the only one differing from the baseline (CRT = 0). Moreover, players with CRT = 3 played more equilibrium responses than CRT = 2 players (linear combination of coefficients, CRT = 3 – CRT = 2, B = 1.07, p = .008) and marginally more than CRT = 1 players (linear combination of coefficients, CRT = 3 – CRT = 1, B = 0.71, p = .091).

Proportion of equilibrium responses	B	SE	t	p	95 % CI	
CRT = 1	0.45	0.38	1.18	.243	- 0.32	1.22
CRT = 2	0.10	0.35	0.29	.772	- 0.60	0.81
CRT = 3	1.17	0.38	3.05	.004	0.40	1.94
N. obs.	48					

Table 2.2. Linear regression of proportion of equilibrium response in DSO games, with CRT score as group factor. CRT = 0 serves as baseline.

As expected, given the ceiling effect of performance in DSS games, CRT score did not have effect on the proportion of equilibrium responses in DSS games, either treating CRT score as continuous variable (B = 0.18, p = .230, Table S2.1 in section 7.2.1, Appendices) or group factor (baseline: CRT = 0. CRT = 1, B = 0.64, p = .127; CRT = 2, B = 0.59, p = .122; CRT = 3, B = 0.45, p = .278. Table S2.2 in section 7.2.1, Appendices).

Then we tested whether the CRT score was associated with the level of strategic thinking predicted by the Cognitive Hierarchy (CH) model, which describes interactive behavior by a hierarchy of decision rules differing in the number (k) of steps of thinking used. In CH, the frequency distribution f (k) of steps of players is assumed to be Poisson, and its mean and variance is described by a single parameter τ. The higher the τ of a population, the higher its level of strategic sophistication. Therefore, we estimated τ for each of our CRT groups, expecting the value of τ to increase along with the CRT level. As expected, the higher the CRT level, the higher the free parameter τ (CRT = 0, τ = 1; CRT = 1, τ = 1.6; CRT = 2, τ = 1.32; CRT = 3, τ = 2.26). Interestingly, players with CRT = 0 exhibit a τ parameter which expresses the expected behavior of a L1 player, while players with CRT = 3 have a τ parameter reflecting the strategy of a L2 player. Players with CRT = 1 and CRT = 2 lie in between these two levels of strategic behavior. Results of the CH model estimation show that cognitive reflection is indeed associated with level of strategic thinking in our 2x2 games.

In Table 2.3, for each CRT level, we report the group level of strategic thinking (τ) and the average proportion of equilibrium responses in DSS and DSO games for each CRT level. In Figure 2.4, we show boxplots of performance for CRT = 0 and CRT = 3 players.

CRT score	N	τ (CH)	Proportion of equilibrium responses (DSS games)	Proportion of equilibrium responses (DSO games)
CRT = 0	14	1	0.78 (0.19)	0.48 (0.18)
CRT = 1	10	1.6	0.88 (0.13)	0.58 (0.18)
CRT = 2	14	1.32	0.88 (0.14)	0.50 (0.23)
CRT = 3	10	2.26	0.86 (0.18)	0.74 (0.21)

Table 2.3. For each CRT group, we report the parameter τ (CH), which expresses the average group level of strategic thinking in the Cognitive Hierarchy (CH) model, and the average proportion of equilibrium responses in DSS and DSO games (standard deviations in brackets).

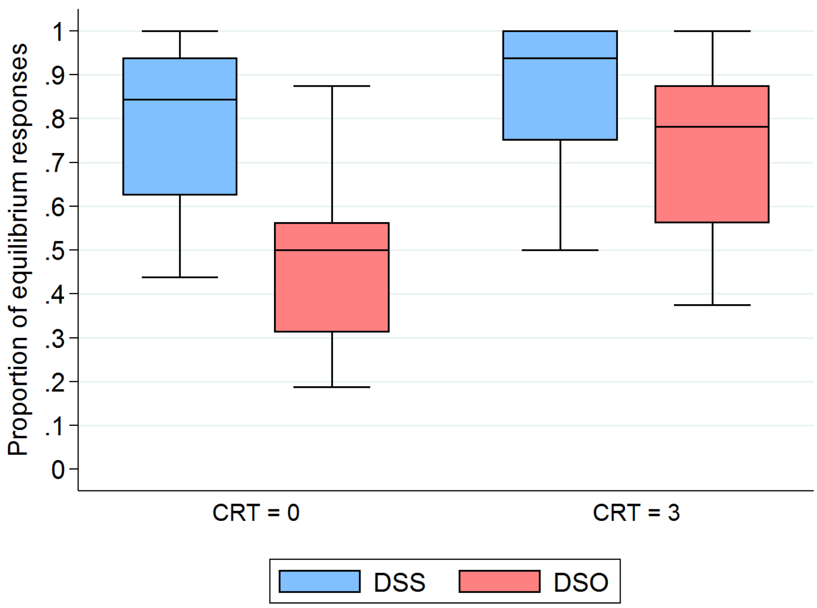

Figure 2.4. Boxplots of proportion of equilibrium responses by game (DSS or DSO) for CRT=0 and CRT=3.

Moreover, we tested whether higher CRT levels are associated with higher earnings. Specifically, we calculated the 'Strategic IQ', defined as the magnitude of the expected payoffs of players given the frequency distribution of actual choices of potential opponents (Bhatt & Camerer, 2005). In other words, the Strategic IQ expresses the optimality of a strategy given the actual distribution of strategies among potential opponents in the population. In our 2x2 games, equilibrium choices in DSO games constitute the best response to L2 and L1 players (but not to L0 players). Given that the distribution of levels of strategic thinking in our sample ranges from L1 (CRT = 0) and L2 (CRT = 3), and that CRT = 3 play the equilibrium strategy more often that lower CRT players, we expect CRT = 3 players to exhibit a higher Strategic IQ than players with lower CRT. In fact, their strategy constitutes the optimal response to the actual distribution of strategic levels in the sample. Results of a regression with Strategic IQ as dependent variable and CRT as factor confirm this prediction: CRT = 3 is the only cognitive reflection level differing from the baseline (CRT = 0) in terms of Strategic IQ ($B = 1.19$, $p = .003$, Table S2.3 in section 7.2.1, Appendices; Figure 2.5). CRT = 3 players also show a higher rate of equilibrium responses when compared to CRT = 2 players (linear combination of coefficients, CRT = 3 – CRT = 2, $B = 1.13$, $p = .005$) and marginally when compared to CRT = 1 players (linear combination of coefficients, CRT = 3 – CRT = 1, $B = 0.77$, $p = .066$). These results suggest that CRT = 3 players had correct beliefs about the distribution of strategic levels in the space of potential opponents, and best respond to this prediction by applying a more sophisticated strategy.

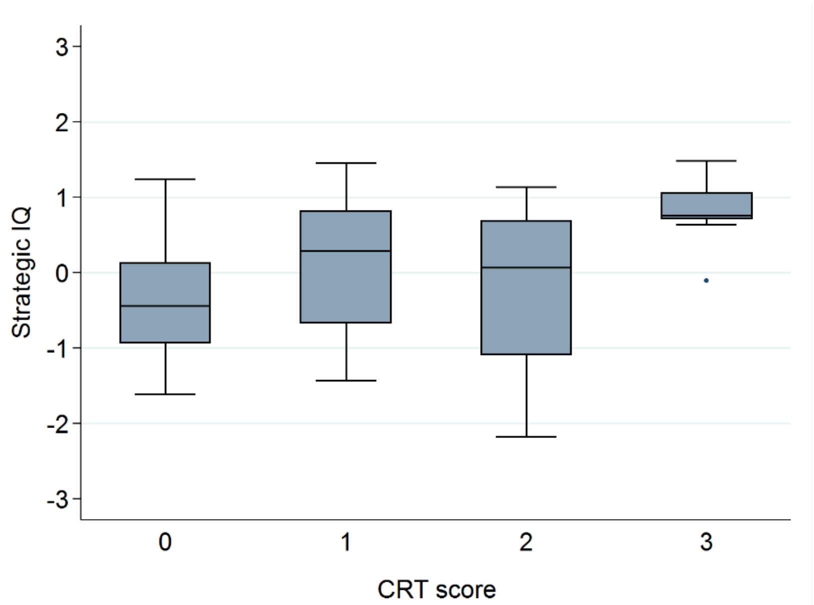

Figure 2.5. Boxplots of proportion of Strategic IQ by CRT score.

Taken together, these results highlight a robust link between cognitive reflection and strategic sophistication.

Gaze patterns and strategic sophistication

In order to individuate the attentional indices able to predict strategic sophistication, we focused on DSO games, since only these games require the evaluation of the opponent's incentives, and heterogeneity in strategic thinking indeed emerges. We ran a mixed-effects logistic regression with equilibrium response as dependent variable, our five types of transition as independent variable and subject as random effect. A low Variance Inflation Factor (VIF) value (1.65) indicated the absence of potential collinearity issues. Results of the model show that strategic behavior is accompanied by a higher proportion of other-payoffs within-action transitions ($B = 0.57$, $p < .001$, Table 2.4) and a lower proportion of own-payoffs within-action transitions ($B = - 0.38$, $p =.005$, Table 2.4). These results confirm that taking into account the incentives of the counterpart and integrating them in an exhaustive model of the interactive problem is fundamental to behave strategically. Specifically, strategic choices were predicted by the tendency to perform other-payoffs within-action transitions, which express the attempt to form precise beliefs about the opponent's choice by computing the expected value of each of the two potential actions of the counterpart. This behavior seems to reflect the search of the highest average payoff for the counterpart, and is consistent with the expected behavior of a Level-2 player that best respond to the belief that the counterpart is Level-1. Conversely, a high rate of own within-action transitions reflects the implementation of a model of choice that does not take into account the rationality of the other player but aims to detect the option with the highest average payoff. This analysis is consistent with the one expected for a Level-1 player (Devetag et al., 2016).

Equilibrium response	B	SE	z	p	95 % CI	
Own-payoffs within-action	- 0.38	0.13	- 2.83	.005	- 0.64	- 0.12
Own-payoffs between-action	- 0.02	0.12	- 0.21	.832	- 0.25	0.20
Other-payoffs within-action	0.57	0.12	4.79	< .001	0.34	0.81
Other-payoffs between-action	0.15	0.10	1.47	.143	- 0.05	0.35
Intra-cell	- 0.12	0.14	- 0.91	.365	- 0.39	0.58
N. obs.	768					
N. independent obs.	48					

Table 2.4. Mixed-effects logistic model of equilibrium response in DSO games, with subject as random effect and the five types of transitions as dependent variables.

CRT and gaze patterns

One of the main goals of the present work is to understand whether cognitive reflection modulates the implementation of sophisticated representations of the game structure. In order to do so, first we test whether the CRT score predicted the sophistication of the visual analysis of DSO payoff matrices. We ran a multivariate regression with our five types of transitions as dependent variables and CRT as independent variable. Results show that CRT score predicted the mean proportion of other-payoffs within-action transitions ($B = 0.45$, $p = .001$, $F = 11.96$, $R^2 = .21$, Table 2.5), which we have previously shown to predict the rate of equilibrium choices. To test for the specificity of the effect of the CRT score on gaze patterns, we also ran stepwise backward regressions including fluid intelligence and working memory measures as independent variables. Results indicated that measured of fluid intelligence and working memory did not have any impact on the average proportion of the five types of relevant transitions (Table S2.4 in section 7.2.1, Appendices). These results were confirmed by a k-fold cross-validation analysis showing that the model that best-predicts the proportion of other-payoffs within-action transitions includes only the CRT as cognitive factor (Lasso coefficient: CRT = 0.10). Figure 2.6 reports scatterplots of the five cognitive measures and the proportion of other-payoffs within-action transitions.

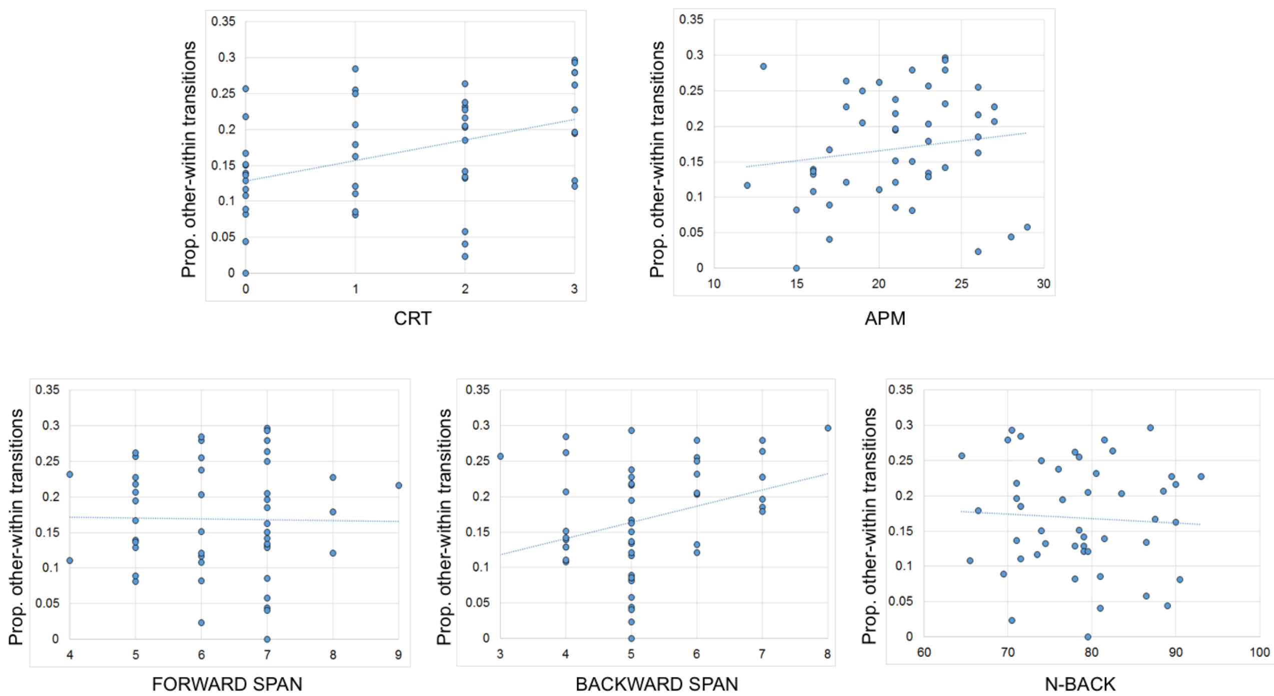

Figure 2.6. Scatter plots of the five cognitive measures and the proportion of other-payoffs within-action transitions in DSO games.

Proportion of transitions	B	SE	t	p	95 % CI	
Own within-action						
CRT score	-0.10	0.15	-0.65	.520	-0.39	0.20
Own between-action						
CRT score	0.03	0.15	0.20	.841	-0.27	0.33
Other within-action						
CRT score	0.45	0.13	3.46	.001	0.19	0.72
Other between-action						
CRT score	0.07	0.15	0.45	.658	-0.23	0.36
Intra-cell						
CRT score	-0.05	0.15	-0.34	.733	-0.35	0.25
N. obs.	48					

Table 2.5. Multivariate regression with the five types of relevant transitions as dependent variable and CRT score as independent variable. We considered DSO games only.

We therefore tested the selective effect cognitive reflection on other-payoffs within-action transitions, treating the CRT as group factor. The model accounted for 23 % of the variability in proportion of other-payoffs within-action transitions ($F(3, 44) = 4.35$, $p = .009$, $R^2 = .23$). We can see that the only CRT level that is significantly different from the baseline (CRT = 0) is CRT = 3 (B = 1.35, p = .001, Table 2.6). CRT = 3 is also different from CRT = 2 (linear combination of coefficients, CRT = 3 – CRT = 2, B = 0.77, p = .048) and marginally from CRT = 1 (linear combination of coefficients, CRT = 3 – CRT = 1, B = 0.82, p = .051).

Prop. other within-action transitions	B	SE	t	p	95 % CI	
CRT = 1	0.54	0.38	1.44	.157	- 0.22	1.30
CRT = 2	0.59	0.34	1.72	.092	- 0.10	1.28
CRT = 3	1.36	0.38	3.61	.001	0.60	2.11
N. obs.	48					

Table 2.6. Linear regression of proportion of other-payoffs within-action transitions in DSO games and CRT score as factor.

These results suggest that the cognitive process characterizing high CRT players (CRT = 3) relies more on the formation of beliefs about the opponent's potential actions, which leads to the generation of a more comprehensive representation of the interactive problem and more sophisticated models of choice (Level-2). This is consistent with previous results (Fehr & Huck, 2016) showing a non-linear relationship between cognitive reflection and strategic sophistication: under a certain cognitive threshold, players do not create expectations about opponent's possible moves and fail to reason strategically.

In figure 2.7 we report an example of visual analysis of a player with CRT = 0 as well as an example of visual analysis of a CRT = 3 player. These examples highlight the marked difference in terms of distribution of attention between own and other-payoff transitions. In Figure 2.8 we show the average distribution of attention across the five types of transitions for high (CRT = 3) and low (CRT = 0) CRT players.

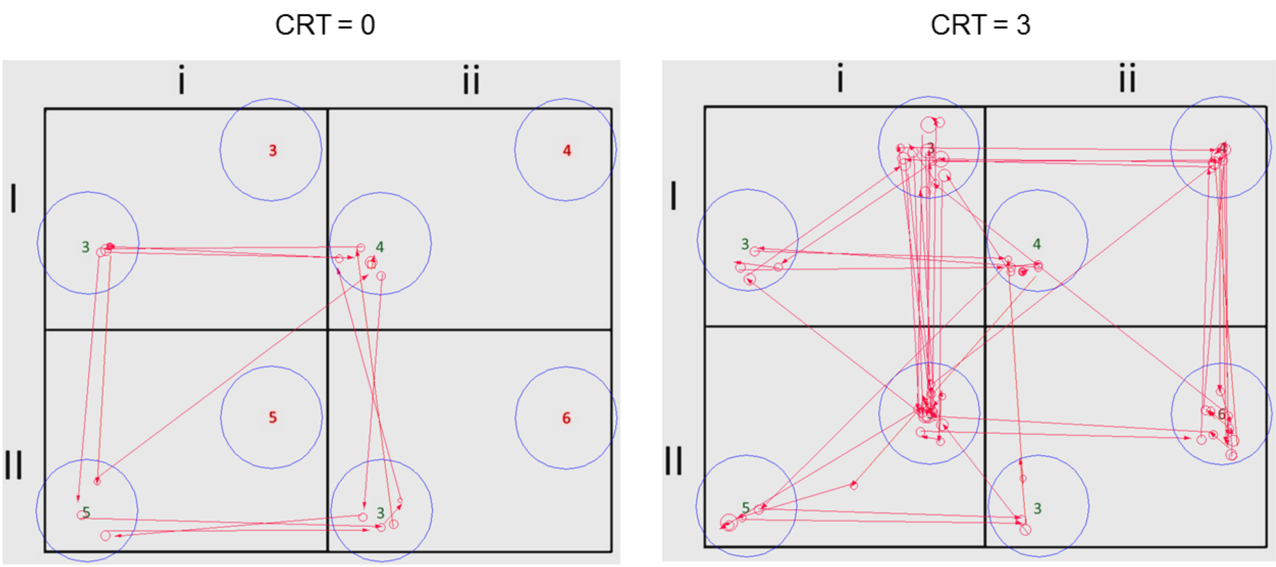

Figure 2.7. Examples of visual analyses of a low CRT (CRT = 0, left panel) and a high CRT (CRT = 3, right panel) player. The low CRT player focuses on own payoffs transitions, while the high CRT player performs a high ratio of other-payoffs within-action transitions to predict the possible choice of the counterpart.

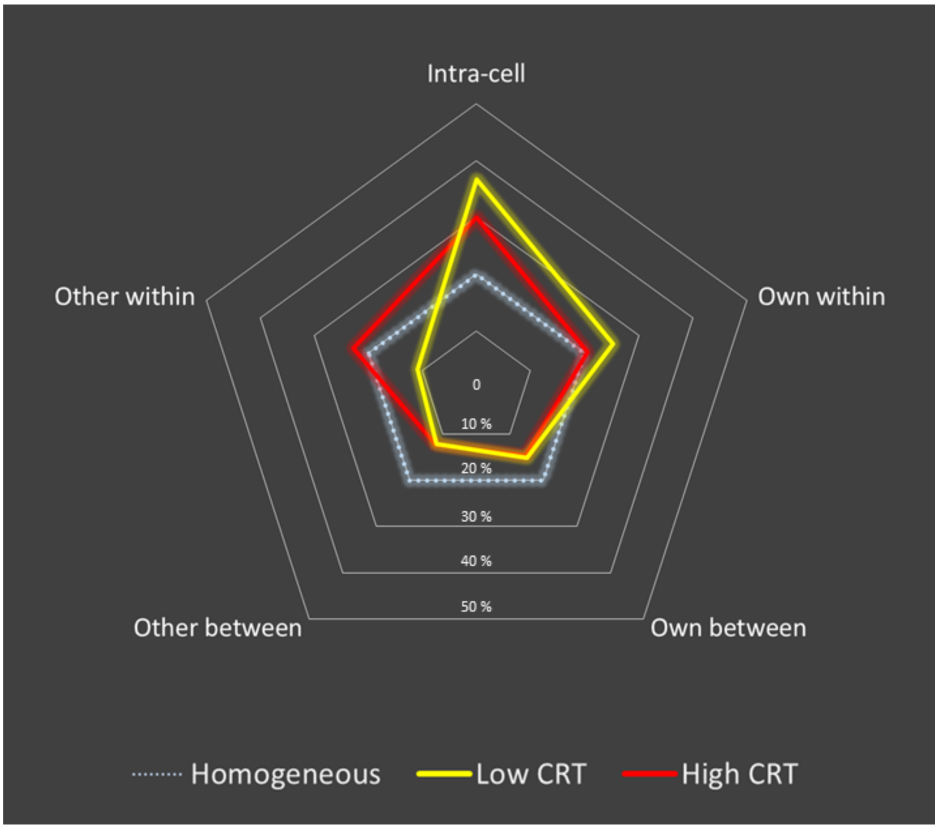

Figure 2.8. Radar chart of average percentage of occurrence the five types of transitions for high CRT (CRT=3) and low CRT (CRT=0) players in DSO games. The dotted line shows the pattern of a perfectly homogeneous distribution of attention. High CRT players distribute attention more homogenously and show a higher percentage of other's payoff within-action transitions (Other within).

The tendency to devote more attention to other's incentives emerges clearly when analyzing the time course of the distribution of attention between own and other's payoffs separately for CRT = 0 and CRT = 3 in DSO games. As shown in Figure 2.9, low CRT players remained primarily focused on their own payoffs during the entire time course of the game. Conversely, high CRT players started focusing on own payoffs, then moved to evaluating incentives of their counterpart, and finally they observed again their own payoffs in order to best respond to the opponent's predicted action. This pattern is consistent with the temporal analysis exhibited by strategic players reported in Polonio et al. (2015).

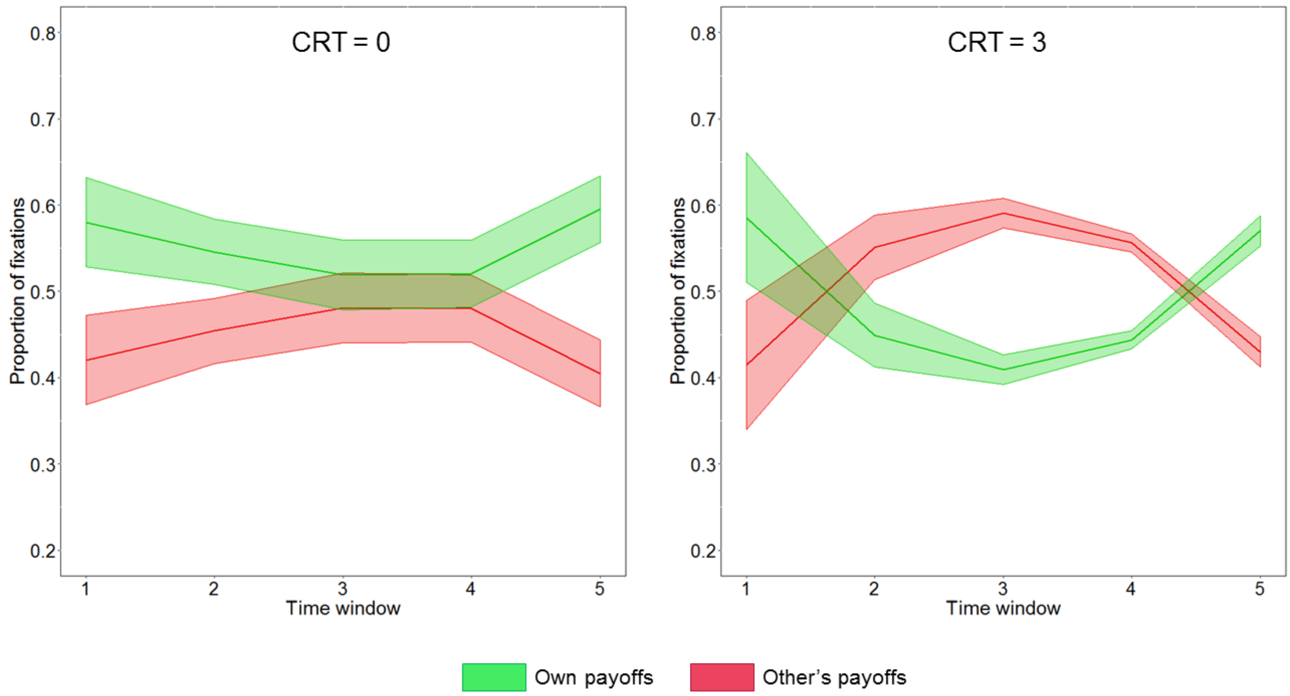

Figure 2.9. Temporal evolution of proportion of own and other's payoffs fixations for CRT = 0 and CRT = 3 in DSO games. In each trial, fixation distribution was normalized across trial time by assigning fixations to five homogeneous intervals based on total number of fixations. In this way, each trial was characterized by five temporal intervals containing equivalent numbers of fixations. Trial-by-trial proportions of fixations 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.

CRT, game representation and strategic sophistication: mediation analysis

In the previous paragraphs, we have shown three main results:

- Visual patterns of information acquisition predicts strategic sophistication in 2x2 games.

- Cognitive reflection predicts strategic sophistication in 2x2 games.

- Cognitive reflection predicts visual patterns of information acquisition in 2x2 games.

Afterwards, we investigated whether the relationship between cognitive reflection and strategic sophistication was mediated by visual analysis. To test this hypothesis, we ran an additional linear regression with proportion of equilibrium responses as dependent variable and CRT score and proportion of other-payoffs within-action transitions as independent variables (Table S2.5 (CRT as continuous variable) and Table S2.6 (CRT as group factor) in section 7.2.1, Appendices). Interestingly, the effect of CRT on equilibrium responses (observed in Table 2.1 and Table 2.2) disappeared after including the proportion of other-payoffs within-action transitions as independent variable, indicating full mediation of visual analysis on the relationship between cognitive reflection and strategic sophistication. The mediated effect was tested for significance using the "Mediation" R package (Imai et al., 2010). Confidence intervals were calculated using the bias-corrected and accelerated bootstrap method (BCa) (Di Ciccio & Efron, 1996), a procedure specifically recommended in mediation analysis (Preacher & Hayes, 2008). As expected, the average causal mediation effect of proportion of other-payoffs within-action transitions on the relation between CRT score and proportion of equilibrium responses was statistically significant ($p < .01$, based on 10000 bootstrap samples), accounting for an estimated 58% of the total effect between CRT score and proportion of equilibrium responses (Table 2.7).

Effect	Estimated coefficient	95% CI lower bound	95% CI upper bound	p
Average causal mediation effect (ACME)	0.19	0.07	0.39	< .01
Average direct effect (ADE)	0.14	-0.13	0.37	.30
Total effect	0.33	0.04	0.57	.02
Proportion mediated	0.58	0.27	5.56	.02

Table 2.7. Results of Causal Mediation Analysis with proportion of other-payoffs within-action transitions as a mediator, CRT score as independent variable and proportion of equilibrium responses as dependent variable.

3.2.4 Discussion

In Experiment 1, we have shown that cognitive reflection, unlike fluid intelligence or working memory, is closely associated with strategic behavior in one-shot 2x2 matrix games. First, the CRT score predict the free parameter τ, expressing the hierarchical level of sophistication in the Cognitive Hierarchy model, as well as the proportion of equilibrium choices in games with a strict dominance for the opponent. Crucially, the CRT score predicts also the type of visual analysis employed in 2x2 one-shot games. High CRT players explored the incentives of the counterpart in order to predict her choice, while low CRT players tended to focus on their own payoffs without integrating other's incentives in their model of the interactive problem. Specifically, the visual analysis of high CRT relied more on other-payoffs within-action transitions, which express the attempt to evaluate the expected value of each of the counterpart's alternatives. These effects were specifically driven by players scoring 3 out of 3 in the CRT, consistently with previous results (Fehr & Huck, 2016) showing that only participants above a certain cognitive threshold create expectations about opponent's possible moves and best respond to them.

Moreover, gaze patterns fully mediated the relationship between CRT score and proportion of equilibrium responses. These results disclose the nature on the relationship between cognitive reflection and strategic sophistication, reported in recent studies (Carpenter et al., 2013; Fehr & Huck, 2016; Georganas et al., 2015; Hanaki et al. 2016; Kiss et al., 2016). Specifically, cognitive reflection does not seem to have any direct effects on choice, but rather modulates the ability to implement a sophisticated visual analysis of the payoff matrix, allowing the generation of comprehensive representations of the interactive problem.

In order to understand the generalizability of these effects, in Experiment 2 we will explore the relationship between cognitive reflection, gaze patterns and strategic choices in matrix games characterized by a more complex payoff structure.

3.3 Experiment 2

3.3.1 Methods

Participants and procedure

Participants were other 48 students from the University of Trento, Italy (27 females, mean age 23, SD 3.16). The study was approved by the local ethics committee and all participants gave informed consent. Participants performed fourteen 3x3 one-shot matrix games. Before playing the games, participants were instructed on the procedure and were provided with examples and training trials (4 games). Moreover, control questions were administered to verify that task and procedure of payment had been fully understood by participants. If participants failed to answer control questions, instructions were repeated until participant's full comprehension (we report detailed instructions and control questionnaires in section 7.3 of the Appendices). The order of games was randomized across participants. Each trial was preceded by a fixation-point positioned in one of four possible locations outside the symbol space.

All participants played in the role of row player and were instructed to choose between row I, row II and row III by key-press.[19] Each game was played only once and no feedback was provided at the end of games. At the end of the fourteen games, three games were randomly selected and the player's choice in each game was paired with the choice of another player in that game. Participants received the sum of the outcomes of the three games in euros (from 3.1 to 29 euros).

Moreover, participants completed the Cognitive Reflection Test (CRT) with the same modalities of Experiment 1. We did not collect other control measures of fluid intelligence and working memory,

[19] In order to pair each participant with an opponent, the 14 games included seven pairs of isomorphic games. Isomorphic games are equivalent in the sense that the second game of each pair is identical to the first except for transposing the players' roles, changing the order of the three actions (for both players), and adding or subtracting a small constant amount from the payoffs of each game. In this way, it was possible to match the choices of row players as they have played in two different roles.

since in Experiment 1 we have already shown that the effect of the CRT on strategic choices or gaze patterns in one-shot matrix games is not driven by covariates such as measures of fluid intelligence or working memory.

3x3 Matrix Games

We used the 14 games reported in Costa-Gomes and Weizsäcker (2008).[20] All games have a unique pure-strategy equilibrium and do not have salient payoffs. Ten of these games are solvable in two, three, or four steps of iterated dominance,[21] while four games have unique Nash equilibrium without dominant strategies (Figure 2.8). All 14 games require strategic sophistication, since no equilibrium response is achievable by considering own payoffs only.

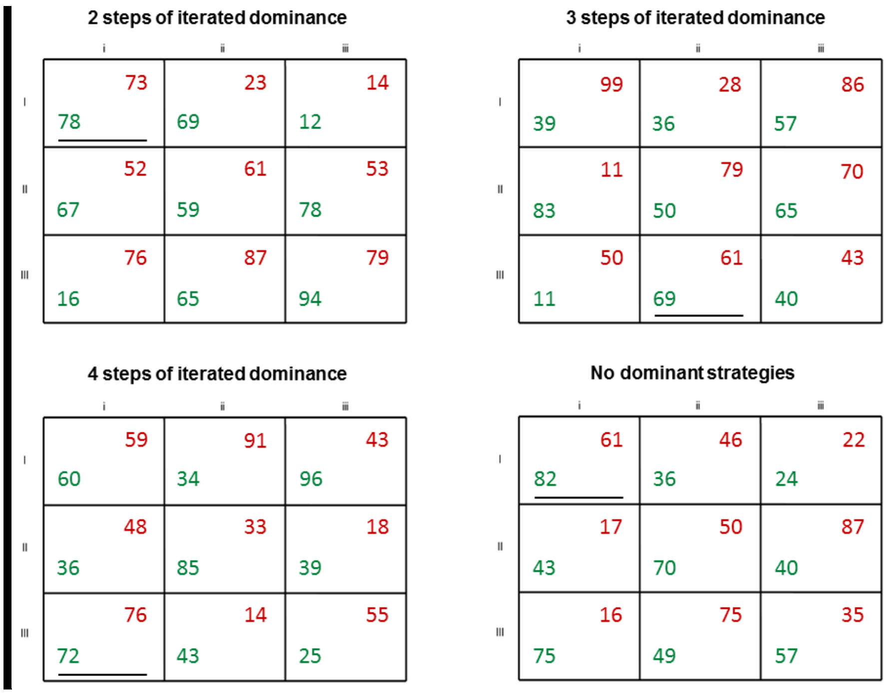

Figure 2.8. Game types in Experiment 2. The line in one of the cells of each matrix signals the equilibrium solution of the game.

[20] For the full game list, see Figure S3.7 in section 7.3.2, Appendices

[21] Four Games are dominance solvable with two rounds of dominance; five games are dominance solvable with three rounds of dominance; one game is dominance solvable with four rounds of dominance.

Eye-tracking procedure and gaze data analysis

The eye-tracking procedure was identical to the one used in Experiment 1.

Concerning gaze data analysis, we defined 18 regions of interest (ROIs) centered on the matrix payoffs. All the ROIs had a circular shape with a size of 36000 pixels, did not overlap and covered 38.8 % of the game matrix area. However, the large majority of fixations (86 %) fell inside the ROIs. All the fixations falling outside the ROIs were discarded.

The same gaze variables of Experiment 1 (own and other's payoffs fixations;[22] five types of between-payoffs transitions) were used for eye-tracking analysis in Experiment 2.

3.3.2 Hypotheses

In Experiment 2, we investigated whether the effects observed in Experiment 1 could generalize to more complex payoff structures (3x3). Recent evidence (Costa-Gomes and Weizsäcker, 2008) has shown that players rarely reach equilibrium in these complex games; rather, they usually implement a maximum of two steps of strategic thinking (level-2) (Polonio & Coricelli, 2018). We do not expect players to regularly play the equilibrium strategy, and the most sophisticated model of choice employed by players should be level-2, which assumes the counterpart to be a level-1 player. We therefore predict the CRT score to be associated with higher levels of strategic thinking (i.e. level-2), and with a higher proportion of level-2 choices.

We also hypothesize that the behavior of high CRT players translates in visual patterns of information acquisition meant to predict the opponent's move: in particular, sophisticated players should exhibit a higher rate of other-payoff within-action transitions, reflecting the attempt to individuate the action with the highest average payoff for the opponent (Bhatt & Camerer, 2005; Costa-Gomes et al., 2001; Devetag et al., 2016; Polonio & Coricelli, 2018). We also predict high CRT players to show a better-

[22] As in Experiment 1, a fixation was defined as an interval in which gaze was focused within 1° of visual angle for at least 100 ms (Manor and Gordon, 2003).

defined temporal pattern of information acquisition in respect to low CRT players. While low CRT players should be focused on own payoffs for the entire game play, high CRT players should start with the evaluation of own payoffs, then move their attention towards the counterpart's incentives to predict her move, then come back to focus on own payoffs to best respond to their prediction.

Finally, we expect sophistication in the visual analysis of the game matrix to mediate the relationship between cognitive reflection and strategic choices.

3.3.3 Results

Behavioral results

In Table 2.8 we report the proportion of choices in accordance with three common models of choices: level-1 (L1) and level-2 (L2) of the Cognitive Hierarchy model, and Nash equilibrium. Consistently with previous results (Costa-Gomes and Weizsäcker, 2008; Polonio & Coricelli, 2018), the model that best explained the average behavior of players in the sample is L1, while players play the Nash equilibrium barely above chance level. In the next paragraph, we will explore whether and how cognitive reflection can account for heterogeneity in strategic sophistication.

Game ID	Behavioral model of choice		
	L1	L2	Nash
1	0.40	0.29	0.29
2	0.50	0.25	0.50
3	0.69	0.21	0.21
4	0.75	0.75	0.25
5	0.56	0.35	0.35
6	0.90	0.90	0.10
7	0.38	0.33	0.33
8	0.58	0.58	0.58
9	0.71	0.25	0.71
10	0.40	0.35	0.35
11	0.58	0.35	0.35
12	0.71	0.71	0.21
13	0.73	0.23	0.73
14	0.50	0.38	0.13
Average	0.60	0.42	0.36

Table 2.8. Average proportion of choices in accordance with each of the three common models of choice (Level-1 (L1), Level-2 (L2) and Nash Equilibrium (Nash).

CRT and strategic sophistication

As in Experiment 1, we estimated the parameter τ of each of the four CRT groups to investigate whether the CRT score is associated with the level of strategic thinking predicted by the Cognitive Hierarchy model. As in the previous experiment, higher CRT levels are associated with higher τ parameters (CRT = 0, τ = 0.59; CRT = 1, τ = 1.40; CRT = 2, τ = 1.12; CRT = 3, τ = 1.54), suggesting a close association between cognitive reflection and level of strategic sophistication (Table 2.9). We can see that τ levels are lower than the ones observed in Experiment 1, as expected by the higher complexity of the games. Specifically, the CRT group with the highest average τ (CRT = 3) exhibited a level of strategic thinking between L1 and L2, confirming that in these games players generally implement a maximum of two steps of strategic thinking. For this reason, we will use the proportion of L2 responses as a behavioral measure of level of sophistication in the next analyses. Average proportions of L2 responses for each CRT level are reported in Table 2.9.

CRT score	N	τ (CH)	Average proportion of L2 responses
CRT = 0	14	0.59	0.32 (0.11)
CRT = 1	9	1.40	0.42 (0.15)
CRT = 2	8	1.12	0.41 (0.23)
CRT = 3	17	1.54	0.52 (0.19)

Table 2.9. For each of the four CRT levels, we report the parameter τ (CH), which reflects the average number of steps of strategic thinking in the Cognitive Hierarchy (CH) model, and the average proportion of L2 responses. Values in brackets represent standard deviations.

The proportion of L2 choices in 3x3 games was modulated by CRT score (Linear regression, B = 0.41, p = 0.003, F(1, 46) = 9.48, R^2 = 0.17, Table 2.10).[23] Then we ran an additional regression (Table 2.11) treating the CRT score as group factor to explore selective effect of each CRT level on choices (linear model, F(3, 44) = 3.33, p = .028, R^2 = 0.19). As in the previous experiment, we found that the only CRT level differing from the baseline level (CRT = 0) is CRT = 3 (B = 0.85, p =.001). We did not find differences between CRT = 3 and the two middle CRT scores (linear combination of coefficients, CRT = 3 – CRT = 2, B = 0.45, p = .141; CRT = 3 – CRT = 1, B = 0.41, p = .166), suggesting that the non-linearity of the relationship between CRT score and choices in 3x3 games is less pronounced than the one found in 2x2 games. This is probably due to the lower mean level of strategic thinking of the CRT = 3 group, that lies between L1 and L2 (τ = 1.54).

[23] The same analysis did not return any significant results when using the proportion of equilibrium responses as dependent variable (B = 0.15, p = .290, Table S3.7 in section 7.3.2, Appendices). This can be easily explained by the low rate of equilibrium responses, which approaches chance level.

Proportion of L2 responses	B	SE	t	p	95 % CI	
CRT score	0.41	0.13	3.08	.003	0.14	0.68
N. obs.	48					

Table 2.10. Linear regression of proportion of L2 responses. The CRT score is the independent variable.

Proportion of L2 responses	B	SE	t	p	95 % CI	
CRT = 1	0.54	0.40	1.35	.184	- 0.27	1.34
CRT = 2	0.48	0.41	1.17	.248	- 0.35	1.32
CRT = 3	1.06	0.34	3.15	.003	0.38	1.74
N. obs.	48					

Table 2.11. Linear regression with proportion of L2 responses as dependent variable, and CRT score as group factor.

In Experiment 1, we have shown that high CRT score (CRT = 3) was associated with a higher level of Strategic IQ. In Experiment 2, we did not observe any association between CRT score and Strategic IQ (Table S2.8 in section 7.2.2, Appendices). The absence of a significant effect in Experiment 2 could be explained by the increase of the strategy space in 3x3 games. In fact, in Experiment 1, the L2 strategy constituted a best response to both L1 and L2 strategies; since the minimum number of steps of strategic thinking observed in 2x2 games was one (L1), the L2 strategy constituted a best response to the large majority of potential opponents in the population. Therefore, players that implemented more often the L2 strategy (CRT = 3) exhibited a higher Strategic IQ. Conversely, in our 3x3 games, the L2 model of choice does not constitute a best response to a L2 or a L0 counterpart and the L2 strategy is not always efficient given the actual distribution of types of players in the population. In other words, in 3x3 games, the heterogeneity of the population's strategy space might have prevented high CRT players from best responding to a high ratio of potential opponents, and from increasing their Strategic IQ significantly.

Gaze patterns and strategic sophistication

To explore the relationship between attentional patterns and choices, we ran a mixed-model logistic regression with L2 response as dependent variable, our five types of transition as independent variable and subject as random effect (Table 2.12). A low VIF value (2.39) indicated the absence of potential collinearity issues. The model confirmed results of Experiment 1, showing that the higher levels of strategic sophistication were accompanied by a higher proportion of other-payoffs within-action transitions ($B = 0.67$, $p < .001$). Additionally, we found an effect of own-payoffs between-action transitions ($B = 0.22$, $p = .019$).[24] The higher proportion of own-payoffs between-action transitions is consistent with the expected and observed visual pattern of information acquisition of strategic players (Polonio & Coricelli, 2018) who, after having formed beliefs about the expected action of the opponent, best respond to this prediction by looking at their own payoffs within the expected counterpart's action.[25] These results confirm that exploring the incentives of the counterpart and integrating them in a comprehensive representation of the game is crucial to exhibit more sophisticated models of choice, as L2.

[24] As expected, given the low proportion of equilibrium responses in our sample, we did not find any effect of type of payoff transitions on the rate of equilibrium responses (Table S3.9 in section 7.3.1, Appendices)

[25] The absence of an effect of own-payoffs between-action transitions in Experiment 1 corroborate previous results (Devetag et al. 2016; Polonio & Coricelli, 2018) showing that an increase in the action space (as in 3x3 matrices) results in a more precise characterization of the gaze patterns underlying the decision process implemented by the participants.

L2 response	B	SE	Z	p	95 % CI	
Own-payoffs within-action	- 0.10	0.16	- 0.66	.510	- 0.43	0.21
Own-payoffs between-action	0.22	0.09	2.35	.019	0.04	0.41
Other-payoffs within-action	0.67	0.13	5.08	< .001	0.41	0.93
Other-payoffs between-action	- 0.06	0.10	- 0.65	.514	- 0.26	0.13
Intra-cell	0.07	0.15	0.46	.642	- 0.22	0.35
N. obs.	670					
N. independent obs.	48					

Table 2.12. Mixed-effects logistic model (subject as random effect). L2 response is the dependent variable, and the five types of relevant transitions are the independent variables.

CRT and gaze patterns

We tested whether the CRT score predicted visual patterns of information acquisition also in 3x3 games. Consistently with results of Experiment 1, CRT score specifically predicted the mean proportion of other-payoffs within-action transitions among the five relevant transitions (Multivariate regression, B = 0.37, p = .009, F (1, 46) = 7.48, R^2 = 0.14, Table 2.13). Then we tested the effect of each of the CRT levels in predicting the mean proportion of other-payoffs within-action transitions (linear model with CRT as group factor, F (3, 44) = 2.56, p = .067, R^2 = 0.15, Table 2.14). We show the only CRT level that differ from the baseline (CRT = 0) is CRT = 3 (B = 0.79, p = .004). However, results do not show any differences between CRT = 3 and the two middle CRT scores (linear combination of coefficients, CRT = 3 – CRT = 2, B = 0.40, p = .216; CRT = 3 – CRT = 1, B = 0.41, p = .196). Such results confirm that a specific level of the CRT score (CRT = 3) predicts the implementation of a specific gaze pattern, characterized by the evaluation of the incentives of the counterpart to form beliefs about her choice (Figure 2.9).

Proportion of transitions	B	SE	t	p	95 % CI	
Own within-action						
CRT score	-0.23	0.14	-1.58	.121	-0.39	0.20
Own between-action						
CRT score	-0.03	0.15	-0.19	.850	-0.27	0.33
Other within-action						
CRT score	0.37	0.14	2.73	.009	0.19	0.72
Other between-action						
CRT score	0.27	0.14	1.94	.059	-0.23	0.36
Intra-cell						
CRT score	-0.12	0.15	-0.84	.405	-0.35	0.25
N. obs.	48					

Table 2.13. Multivariate regression, the five types of relevant transition are the dependent variables, and the CRT score is the independent variable.

Prop. Other-payoffs within-action transitions	B	SE	t	p	95 % CI	
CRT = 1	0.47	0.41	1.15	.258	- 0.35	1.29
CRT = 2	0.47	0.42	1.10	.275	- 0.38	1.32
CRT = 3	0.95	0.34	2.76	.008	0.26	1.64
N. obs.	48					

Table 2.14. Linear regression of proportion of other-payoffs within-action transitions with CRT as group factor. Baseline: CRT = 0.

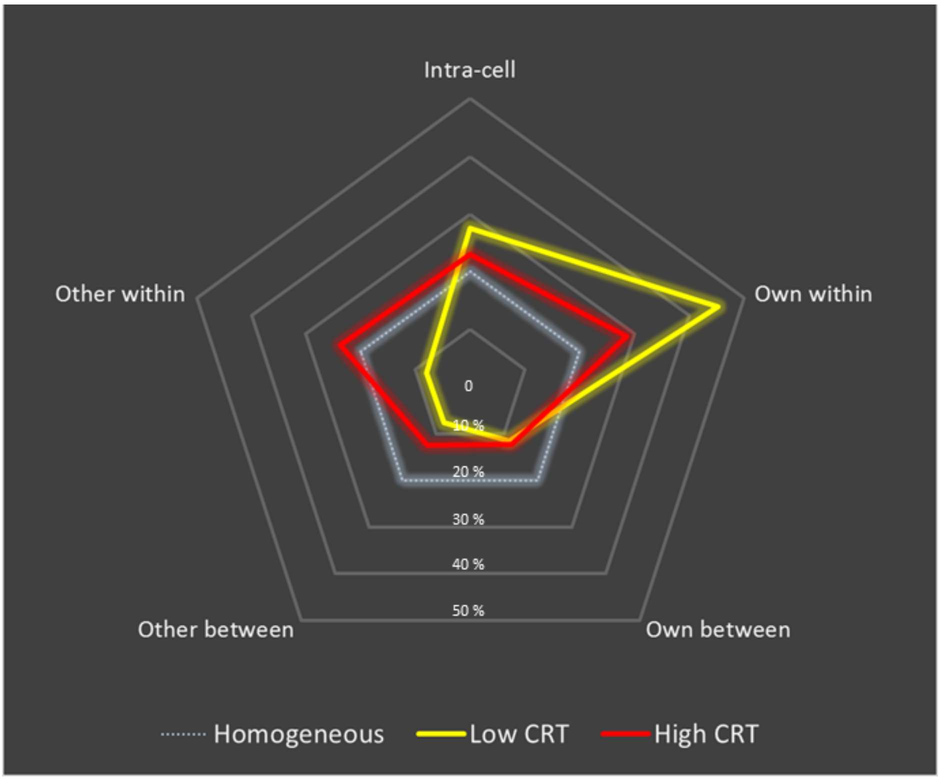

Figure 2.9. Radar chart showing the average percentage of occurrence of the five types of relevant transitions for high CRT (CRT = 3) and low CRT (CRT = 0) players in Experiment 2. The dotted line reflects the pattern of a perfectly homogenous distribution of attention. High CRT players distribute attention more homogenously and exhibit a higher percentage of other's payoff within-action transitions (Other within) when compared to low CRT players. Conversely, low CRT participants have a strong attentional bias on Own-payoffs within-action transitions (Own within).

We also plotted the time course of the distribution of attention between own and other's payoffs separately for CRT = 0 and CRT = 3 players. As shown in Figure 2.10, low CRT players were primarily focused on their own payoffs during the entire time course of the game. Conversely, high CRT players started focusing on own payoffs, then increased their level of attention towards the payoff of the counterpart and, before making a decision, they focused again their own payoffs in order to best respond to the opponent's predicted action (Polonio et al., 2015). The temporal pattern of high CRT players is less neat than the one observed in Experiment 1, probably due to the increased complexity of the payoff structures that generally pushes players to focus more on own payoffs and play less sophisticated strategies in 3x3 games.

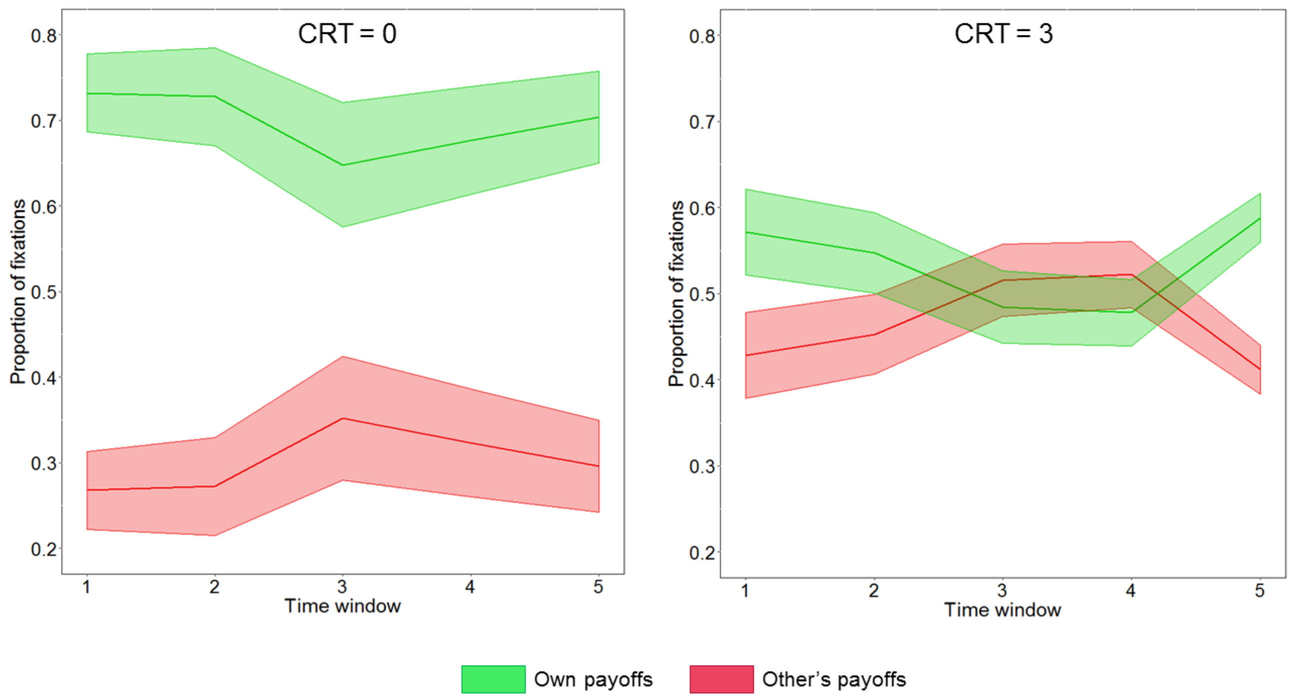

Figure 2.10. Temporal evolution of the distribution of attention between own and other's payoffs fixation for CRT = 0 and CRT =3 players. As in Experiment 1, we normalized trial-by-trial fixation distribution across trial time, by assigning fixations to five homogeneous intervals containing equivalent numbers of fixations. We averaged trial-by-trial proportions for each participant, and then we averaged individual time courses across participants. Filled areas around lines represent between-subject standard errors of the mean.

CRT, game representation and strategic sophistication: mediation analysis

Finally, we aimed to replicate findings from Experiment 1, showing an effect of full mediation of game visual analysis on the relationship between cognitive reflection and sophistication of choices. Therefore, we ran a linear regression with mean proportion of L2 response as dependent variable and CRT score and proportion of other-payoffs within-action transitions as dependent variables (Table S2.10 (CRT as continuous variable) and Table S2.11 (CRT as group factor) in section 7.2.2, Appendices). As in Experiment 1, after including the proportion of other-payoffs within-action transitions as independent variable, the effect of CRT on L2 responses disappeared, indicating full mediation of game visual analysis on the relationship between cognitive reflection and strategic choices. The average causal mediation effect of proportion of other-payoffs within-action transitions on the relation between CRT score and proportion of L2 responses was statistically significant ($p = .01$, based on 10000 bootstrap samples, bias-corrected and accelerated bootstrap method), accounting for an estimated 68% of the total effect between CRT score and L2 responses (Table 2.15).

Effect	Estimated coefficient	95% CI lower bound	95% CI upper bound	p
Average causal mediation effect (ACME)	0.28	0.11	0.50	< .01
Average direct effect (ADE)	0.13	-0.04	0.32	.14
Total effect	0.41	0.18	0.65	< .01
Proportion mediated	0.68	0.37	1.17	< .01

Table 2.15. Results of Causal Mediation Analysis with proportion of other-payoffs within-action transitions as a mediator, CRT score as independent variable and L2 responses as dependent variable.

3.3.4 Discussion

In Experiment 2, we have replicated results of Experiment 1 using different types of game (3x3 matrix games), characterized by increased relational complexity of the payoff structure. As in the previous experiment, a high CRT score was associated with the tendency to take into consideration other's incentives, and predicted the implementation of more sophisticated models of choice (closer to level-2 of the Cognitive Hierarchy model). Moreover, the relationship between cognitive abilities and strategic choices was entirely driven by the mediating effect of the type of visual analysis implemented. Eye-tracking and behavioral results support the idea that strategic thinking of players is in some measure bounded, consistently with previous findings (Costa-Gomes and Weizsäcker, 2008). In fact, participants rarely chose in accordance with the equilibrium strategy, or performed a visual analysis consistent with the expected equilibrium solution procedure. Players with a high CRT score (CRT = 3) used a strategy closer to Level-2 (τ = 1.54) when compared to the other CRT levels (τ ranging from 0.59 to 1.400). Consistently, analysis of gaze data confirm that the best predictor of strategic behavior was the tendency to perform a high proportion of other-payoffs within-action transitions, expressing the attempt to compare other's incentives within the same choice in order to predict her forthcoming action. The CRT score was a strong predictor of this characteristic of the game visual analysis: high CRT players successfully incorporated incentives of other agents in their model of choice, while low CRT agents lacked the necessary integration between own and other's incentives. This is in line with the concept of 'strategic awareness' advanced by Fehr and Huck (2016), who observed that participants under a certain cognitive threshold did not engage in any type of strategic thinking in the Beauty Contest Game. Moreover, the implementation of other-payoffs within-action transitions completely mediated the relationship between CRT score and strategic choice, underlying the centrality of game representation processes in explaining recent results (Carpenter et al., 2013; Fehr & Huck, 2016; Georganas et al., 2015; Hanaki et al. 2016; Kiss et al., 2016) showing a correlation between cognitive reflection and economic behavior in games.

3.4 Study 2: general discussion

In two eye-tracking experiments, we have shown that cognitive reflection can predict the ability to take into account others' incentives in the visual analysis of the payoff matrix, integrating them in a comprehensive model of the interactive problem. This characteristic of game visual analysis is fundamental since reflects the attempt to make predictions about other's actions and best respond to such beliefs, which we can consider as the hallmark of strategic behavior. High levels of cognitive reflection also explained the implementation of a higher number of steps of strategic thinking in the decision process, in the framework of Level-k and Cognitive Hierarchy theories. Interestingly, the relationship between cognitive reflection and strategic choices was completely mediated by gaze patterns, underlying a precise role for cognitive reflection and game representation mechanisms in explaining strategic behavior.

The observed association between cognitive reflection and lookup patterns suggests that one of the causes underlying unsophisticated strategic behavior lies in the inability to process and represent relevant information accurately. Individuals characterized by an unreflective cognitive style tend to disregard relevant pieces of information about others' incentives, to form inaccurate beliefs about the action of the counterpart, and to choose with less sophisticated models of choice. However, this does not imply that low CRT players are unable to attribute mental states to other; rather, it suggests that cognitive reflection modulates top-down attentional process of information search and representation necessary to correctly integrate others' incentives in the model of the opponent's decision space. When the complexity of this cognitive operation is high, low cognitive reflection agents may implement a simple behavioral rule that simplify the relational structure of the problem (Devetag & Warglien, 2008; Pantelis & Kennedy, 2017). For instance, they may focus primarily on own payoffs (Evans & Krueger, 2014), as also suggested by the increased bias towards own payoff in in Experiment 2. We believe that our results shed new light on the cognitive mechanisms underlying the emergence of hierarchical levels of strategic thinking, as described by theories of bounded rationality such as Level-K and Cognitive Hierarchy. Nonetheless, our findings highlight a crucial component of the concept of 'strategic awareness' advanced by Fehr & Huck, 2016. Specifically, the authors suggested that out-of-equilibrium behavior is driven by the lack of understanding of the interactive nature of the game: we indeed propose that a potential cause of this 'strategic awareness' lies in the inability to process task-relevant information exhaustively.

Interestingly, we did not find a relationship between cognitive factors such as fluid intelligence and working memory and the level of sophistication of choices and visual patterns in one-shot games. We acknowledge that these correlational (null) results have been obtained in a limited sample size (N=48, Experiment 1) and must be therefore interpreted with caution. Furthermore, the absence of an effect of fluid intelligence (APM test) on strategic sophistication can appear in contrast with previous studies (Gill & Prowse, 2016; Burks et al., 2009). However, it must be noted that these two studies differ from ours in different ways. On the one hand, Gill & Prowse (2016) used a repeated Beauty Contest Game and the effect of fluid intelligence on players' entries indeed emerge only after the first round of the repeated game; in the first round, in a condition comparable to the one of our one-shot games, participants with low and high APM score show similar level of sophistication in choices. The emergence of differences between low and high Raven participants in the following rounds might be due to differences in the process of evaluation of others' feedbacks in the previous round and the consequent processes of updating of entries in the current one. This is consistent with the theory proposed by Shipstead et al. (2016) suggesting a specific involvement of fluid intelligence in updating and inferential mechanisms. On the other hand, Burks et al. (2009) used a sequential Prisoner's Dilemma that involves a strong component of reciprocation, that is absent in our one-shot games, in addition to risk and trust components. Therefore, the differences between the sequential Prisoner's Dilemma proposed by Burks and colleagues and our simple one-shot matrix games may have driven the inconsistency between the two studies in terms of fluid intelligence effects. In line with our results, we highlight that large parts of the studies reporting a relationship between cognitive abilities and choices in the one-shot version of common games like the beauty contest or matrix games used the CRT as cognitive measure of interest (Branas-Garza et al., 2009; Carpenter et al., 2013; Fehr & Huck, 2016; Georganas et al., 2015; Kiss et al., 2016), highlighting the importance of the cognitive constructs expressed by the CRT score in explaining and understanding the cognitive nature of strategic sophistication.

We have also shown that the visual analysis sustaining the construction of game representations completely mediates the relationship between cognitive reflection and strategic choices. This finding is extremely important since it discloses the nature of this effect, widely reported in recent studies exploring the link between game playing and cognitive abilities (Akiyama et al., 2017; Branas-Garza et al., 2009; Carpenter et al., 2013; Fehr & Huck, 2016; Georganas et al., 2015; Kiss et al., 2016). Cognitive reflection does not directly have an impact on choices, but rather influences mechanisms of encoding and representation of relevant information in the payoff matrix, which in turn predict sophistication in choices. Moreover, this finding offers new insight about the role of cognitive reflection and representation-building in higher cognition, given that the CRT has been found to predict behavior in several decision-making (Brañas-Garza et al., 2012; Campitelli & Labollita, 2010; Graffeo et al., 2015; Toplak et al., 2011), learning (Don et al., 2016) and reasoning (Hoppe & Kusterer, 2011; Oechssler et al., 2009) tasks. In particular, these results sustain the idea that the effect of cognitive reflection on complex tasks may root in the mediating effect of processes of search, encoding and representation of task-relevant information, as already suggested in previous studies (Cokely & Kelley, 2009; Sirota et al., 2014).

Taken together, our results stress the importance of processes of representation generation for understanding strategic behavior (Devetag & Warglien., 2008), and ground the sophistication of such processes in the ability to implement either rich or miserly information processing, as reflected by individual levels of cognitive reflection. Nonetheless, we do not exclude that other cognitive processes may intervene in determining sophistication in interactive decisions. For example, abilities in recursive thinking might influence performance in games like the Beauty Contest game (Mazzocco et al, 2013), and forward or backward induction may be necessary in multi-step games. Working memory abilities might influence strategic behavior in repeated games, where information about previous trials must be recalled and integrated with novel information. Furthermore, social motives might intervene in the decision process and influence the expected utility of players with other-regarding preferences, who aim to maximize joint, rather than individuals, outcomes (Devetag et al., 2016; Polonio & Coricelli, 2018).

Since results of Study 2 are purely correlational, in Study 3 we aim to investigate if we can observe some adaptive mechanisms of strategy generation and selection in interactive games. More specifically, we want to test whether participants using unsophisticated information-processing strategies (i.e. who do not perform the relevant payoff comparison to decide strategically) switch gaze patterns and strategy after being exposed to alternative decision rules in the same games. Attentional and behavioral shifts in unsophisticated (non-strategic) participants would suggest that their original mechanisms of strategy generation relied on an incomplete representation of the decision space and the strategy set.

4. Study 3: Does exposure to alternative decision rules change gaze patterns and behavioral strategies in games?

4.1 Introduction

In study 2, we have shown that sophistication of visual analysis and choices in interactive games can be predicted by individual levels of cognitive reflection. In Study 3 we aim to further investigate the drivers of strategic behavior by testing whether players exhibiting less sophisticated visual analyses and models of choice are able and willing to switch strategy after being exposed to alternative models of choice. Deviations from normative game theoretical responses can arise from two different sources. On the one hand, players may implement a limited number of steps of strategic thinking, as described by hierarchical theories of strategic thinking such as Level-k (Crawford 2003; Crawford et al. 2013; Nagel 1995; Stahl & Wilson 1995) and Cognitive Hierarchy (CH, Camerer et al 2004; Chong et al. 2016). As observed in Study 2, heterogeneity in strategic sophistication is associated with processes of encoding and representation of relevant information (e.g. the incentives of the counterpart), which are in turn modulated by individuals cognitive reflection levels.

On the other hand, another stream of research investigated strategic heterogeneity from a non-cognitive perspective. In particular, theories of social preferences (Andreoni & Miller 2002; Bolton & Ockenfels 2000; Fehr and Schmidt 1999; Fisman et al. 2007; Rabin 1993) relaxed the assumption of self-interest implied in traditional game theory, assuming that agents may have other-regarding preferences that modulate their utility function and, therefore, their choices.

In recent years, behavioral research has sought to describe the process underlying different models of choice in game play. In particular, empirical works involving eye-tracking and mouse-tracking successfully characterized different types of players based on their payoff lookup patterns (Brocas et al. 2014, 2018; Costa-Gomes et al. 2001; Devetag et al. 2016; Hristova & Grinberg 2005; Polonio et al. 2015; Polonio & Coricelli 2018). Taken together, results show that sophisticated choices are associated with a specific pattern of information acquisition characterized by the exploration and evaluation of both own and others' incentives. However, some players disregard relevant pieces of information that are necessary to evaluate the incentives of the counterpart and to predict her move and, thus, they apply a limited number of steps of strategic thinking (Costa-Gomes et al. 2001; Polonio et al. 2015). Yet another type of player focuses on intra-cell comparisons between payoffs, framing the problem as a pure coordination game and disregarding dominant choices of the counterpart: this pattern of visual analysis lead to cooperative choices in line with models of social preferences (Devetag et al., 2016).

Although these works successfully describe the processes underlying out-of-equilibrium choices, they do not fully clarify the nature of the observed heterogeneity in gaze patterns. Specifically, we do not know whether level-1 players disregard others' incentives because they do believe that the other players do not have a preferred choice, or if players do not realize that they could play a more sophisticated strategy (Grosskopf & Nagel 2008). At the same time, it is unclear if the emergence of strategies based on intra-cell comparisons is driven by the desire to maximize social well-being, or if it reflects a misrepresentation of the interactive game structure and its interactive nature (Devetag & Warglien 2008).

In order to address these open questions, we run an eye-tracking experiment in which participants are initially asked to play different classes of one-shot 2x2 matrix games with a human counterpart (Phase 1). In Phase 2, they are asked to apply specific decision rules (Level-1, Level-2, and Cooperative) playing the same games with a computer algorithm whose strategy is known, and are paid based on the actual compliance to the current rule. In Phase 3, participants play the same games as in Phase 1 with another human counterpart. We classify players as Level-1, Level-2, and Cooperative types based on their lookup patterns in Phase 1, and then explored changes in the visual analysis of the game matrix in Phase 3, after participants have experienced the three models of choice. We are particularly interested in testing if level-1 and cooperative players change their type of visual analysis of the game matrix and their choices towards the one expected for more sophisticated types (e.g. level-2), after being exposed to the level-2 model of choice. We show that level-1 players switch their type of visual analysis towards the one characterizing level-2 players, devoting more attention to the counterpart's incentives. The attentional shift observed in level-1 players predicts an increase in the proportion of equilibrium responses in games in which the opponent has a dominant action. However, we do not observe general changes in the behavioral strategy of level-1 players, consistently with recent results (Polonio & Coricelli 2018) showing that level-1 players play the level-1 strategy even if they believe their counterpart to have a preferred action. At the same time, cooperative players do not change their patterns of information acquisition and continue to focus on intra-cell comparisons, suggesting that their behavior is driven by other-regarding preferences. Taken together, these results offer new insights on theories of bounded rationality and social preferences.

4.2 Method

Experimental design

100 students from University of Trento (Italy) participated in this study. At the beginning of each experimental phase, we instructed participants about the experimental procedure of the current phase and provided them with examples, control questions and training trials.[26] If participants failed one of the control questions, the instructions were repeated; if they failed the same control question a second time, they were dismissed.

In Phase 1, each participant plays 48 2x2 one-shot matrix games with another randomly-selected participant of the same pool.[27] All participants play in the role of row player and have to choose

[26] We provide the full translation of instructions and control questions in section 7.3 of the Appendices.

[27] In order to pair each participant with a counterpart, the 48 games consist of 24 pairs of isomorphic games where row and column payoffs are identical but switched.

between row I and row II by pressing a button. Each game is played only once and no feedback is provided after each game. The order of the games is randomized across participants.

In Phase 2, participants play with a computer that simulates the behavior of three different agents. Participants perform three different tasks that consist in the application of three different decision rules (Level-1, Level-2 and Cooperative): in each of the three tasks, participants play the same 48 games of Phase 1. All participants play each of the three tasks in random order. In the Level-1 task, participants are told that the computer chooses randomly, and they are asked to provide a best response to the computer strategy by choosing the row with the highest average payoff. In the Level-2 task, they are informed that the computer chooses the column with the highest average payoff, and they are asked to best respond to this prediction by choosing the row that maximizes the player's outcome within the computer's predicted action. In the Cooperative task, participants are informed that the computer attempts to coordinate with the player to maximize the joint outcome, choosing the column containing the cell with the highest average payoff. Given the expected action of the computer, participants are asked to coordinate with the computer by choosing the row containing the cell that maximizes the joint outcome.

In Phase 3, participants play again the same 48 games as in Phase 1. They are informed that they will play with another participant from a separate experimental session involving the same games; they also know that their counterpart has not taken part in Phase 1 and Phase 2, and is not aware that the participants in this experiment have undertaken Phase 1 and Phase 2.[28]

At the end of the three sessions, players are paid based on their choices in the three phases. Specifically, in each of phases 1 and 3, one game is selected randomly and the participant's choice in each game is combined with the counterpart's choice in the same game (1-9 euros in each phase). In Phase 2, participants are paid based on the rate of compliance to the current decision rule (maximum:

[28] In Phase 3, participants are paired with a counterpart who has played the same 48 games in a separate experimental session involving a single round of game play, without any preceding task involving decision rules.

3.36 euros in each rule). The sum of the outcomes in the three phases constitutes the participants' final earnings (ranging from 2 to 28.08 euros).

In total, we excluded five participants due to non-compliance to the task instructions.[29]

Matrix games

We use four classes of 2 x 2 one-shot games (Figure S2.1, section 7.2.1, Appendices). 16 games are dominance solvable "self" games (DSS), in which only the participant (who chooses rows) has a strictly dominant strategy. Other 16 games are dominance solvable "other" games (DSO), in which only the counterpart (who chooses columns) has a strictly dominant strategy. DSS and DSO games have a unique Nash equilibrium. DSO games differ from DSS games because participants need two steps of iterated elimination of dominated strategies to detect the Nash equilibrium. Conversely, DSS games need only one step of iterated elimination of dominant strategies over participant's own actions. Games within each of the two classes vary in terms of magnitude of payoffs and relations between payoffs, but always maintain the described structure of dominance between actions.

We also use 16 games with multiple equilibria. Eight of these games are Stag-Hunt (SH), a coordination game with two equilibria (one of which is Pareto efficient) in which both players can choose between a safe/low return equilibrium and a risky/high return one. The other eight games are Games of Chicken (GOC), an anti-coordination game with two equilibria in which it is mutually beneficial for players to play different strategies.

Eye movements data analysis

[29] Two participants failed for two consecutive times at least one of the control questions of the experiment. Three participants misapplied the Level-2 decision rule in the Level-2 task (Phase 2), exhibiting visual analysis and choices that were inconsistent with the decision rule.

We describe the eye-tracking procedure in detail in section 7.3 of Appendices. We characterize lookup patterns by considering transitions, which consist eye movements from one region of interest to the next. In particular, we focus on those transitions that can reflect the type of visual analysis carried out by participants, as already described in previous works (Devetag et al 2016; Polonio et al. 2015, Polonio & Coricelli 2018). We divide transitions into three major types:

1) own transitions: transitions between player's own payoffs.

2) other's transitions: transitions between the counterpart's payoffs.

3) intra-cell transitions: transitions between the payoffs of the two players, within the same cell.

Each type of transition expresses the encoding of specific pieces of information within the payoff matrix. We analyze the patterns of analysis by pooling data from different types of games, since it has been already shown that patterns of information acquisition are stable across classes of games (Devetag et al 2016; Polonio et al. 2015, Polonio & Coricelli 2018). A high proportion of own transitions has been shown to predict the implementation of the level-1 (L1) strategy, which focuses on the best response to the belief that that the counterpart chooses each action with equal probability. A high proportion of other's transitions is associated with the implementation of level-2 (L2) model of choice, which requires the evaluation of other's incentives in order to predict the counterpart's move. Intra-cell comparisons are used by cooperative players to detect the cell that maximizes the joint outcome.

Following Jiang et al. (2016), we classify our participants in types based on the comparison between their analysis in Phase 1 and the one used to apply the three decision rules in Phase 2. In particular, for each participant, we take proportions of own, other, and intra-cell transitions in Phase 1 and we calculate their Euclidean distance from the participant's proportions of transitions in each of the three tasks of Phase 2. These give us individual measures of distance from L1, L2, and Cooperative visual analyses (L1, L2 and Cooperative distances). Participants are then assigned to types (L1, L2 or Cooperative) based on the lowest between these three distances.

Once we have classified participants in types based on gaze data in Phase 1, we investigate whether their attentional patterns change in Phase 3. In particular, we test if L1 and cooperative players, in Phase 3, switch towards the type of visual analysis typical of L2 play. To address this hypothesis, we focus on changes in L2 distance from Phase 1 to Phase 3: the decrease in L2 distance for L1 and cooperative participants would indicate the increase in the sophistication of their gaze patterns.

4.3 Results

Gaze patterns in Phase 1 and 3

Results of the classification of participants into L1, L2, and Cooperative types based on the gaze patterns in Phase 1 are reported in Table 1. The average distances in Phase 1 obviously reflect the classification in types: the L1 group (n = 19) is best characterized by the shortest distance to the L1 strategy, the L2 group (n = 35) by the shortest distance to the L2 strategy, and the Cooperative group (n = 41) by the shortest distance to the Cooperative strategy. Looking at the distances in Phase 3, we can already observe a notable change in the L1 group, whose L1 and L2 distances are now very close to each other. Conversely, L2 and Cooperative groups seem to maintain similar distances.

Group (Phase 1)	N	Phase 1			Phase 3		
		L1 dist.	L2 dist.	Coop dist.	L1 dist.	L2 dist.	Coop dist.
Level-1	19	0.14 (0.09)	0.39 (0.12)	0.46 (0.13)	0.27 (0.20)	0.28 (0.18)	0.40 (0.17)
Level-2	35	0.37 (0.08)	0.17 (0.05)	0.31 (0.07)	0.39 (0.10)	0.17 (0.09)	0.31 (0.12)
Cooperative	41	0.45 (0.10)	0.29 (0.08)	0.13 (0.08)	0.42 (0.16)	0.30 (0.12)	0.19 (0.16)

Table 2.1. Average distances from the patterns of visual analysis during the application of decision rules in Phase 2 (L1 dist., L2 dist., Coop dist.), divided by Phase (1 and 3) and group (Level-1, Level-2 and Cooperative). Groups are defined based on the gaze data in Phase 1.

We analyze these effects by running a random effects linear regression with errors clustered by subject (robust standard errors) using L2 distance as a dependent variable and dummies for group and phase as independent variables (Table S3.1 in section 7.3, Appendices). Phase 1 and L2 group serve as a baseline. Results show that L1 players decrease their L2 distance significantly more than L2 players, while the effect is absent in the Cooperative group (interaction effects, Table S3.1: Phase 3 x L1 group, B = -0.84, p = .023; Phase 3 x Cooperative group, B = 0.03, p = .839).

Testing linear combination of coefficients, we can observe that only the L1 group shows a significant decrease in the L2 distance from Phase 1 to Phase 3 (B = -0.84, p = .016), while there is no effect of phase in both L2 (B = -0.00, p = .968) and Cooperative (B = 0.03, p = .800) groups.

To test these effects in more details, we analyze between-phase changes in the proportion of relevant transitions (Figure 2.1).

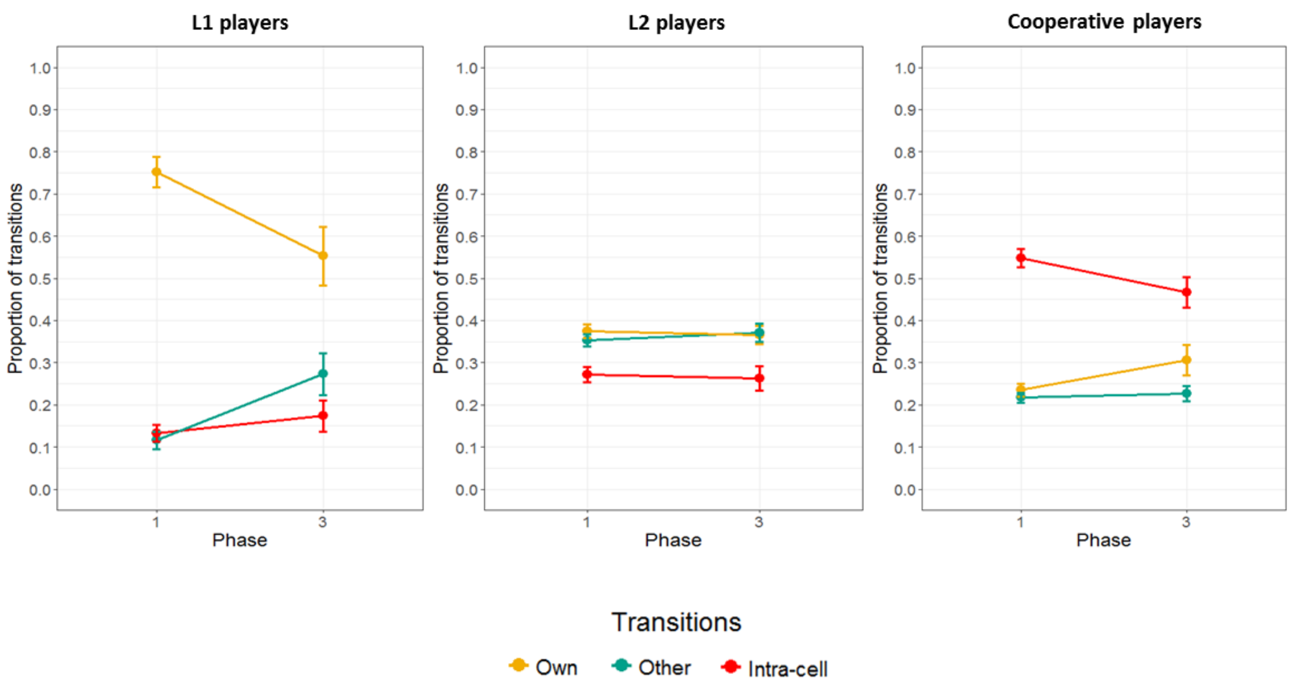

Figure 2.1. Proportion of own, other and intra-cell transitions in Phase 1 and Phase 3 for the three player types.

Specifically, we run three random effects linear regressions with errors clustered by subject (robust standard errors) using as dependent variables the proportions of own, other's and intra-cell transitions, and dummies for group and phase as independent variables (Table S3.2 in section 7.3, Appendices). We use Phase 1 and L2 group as baseline. Consistently with the effect of switch towards the L2 visual analysis (Table 2.1), L1 players increase their proportion of other's transitions (linear combination of coefficients, B = 1.08, p = .004) and decrease their proportion of own transitions (B = -0.77, p = .031). These effects are stronger in L1 players than in L2 players (interaction effects, other: B = 0.85, p =.031; own: B = -0.80, p = 0.033), who in turn do not show any effect of phase on transition proportions (linear combination of coefficients, own: B = 0.03, p = .793; other: B = 0.22, p = .076; intra-cell: B = 0.02, p = .840). The attentional shift of L1 players indicates that the exposure to a more sophisticated rule may increase the focus on the evaluation of the other's incentives to form beliefs about the counterpart's action.

Cooperative players, in Phase 3, exhibit a significant increase in own transitions (B = 0.32, p = .026), but no phase difference in the proportion of other's transitions (B = 0.13, p = .237).[30] The absence of an effect on other's transitions in cooperative players is important to explain their stability in terms of L2 distance across phases. Altogether, our results suggest that cooperative players did not move towards a more sophisticated visual analysis (L2) in Phase 3.

Choices in Phase 1 and Phase 3

In this section, we test whether the switch in visual analysis (i.e. decrease in L2 distance) from Phase 1 to Phase 3 in L1 players is directly associated with a change in players' choices. We consider the proportion of *equilibrium* responses in DSS and DSO games and the proportion of *risk dominant equilibrium* choices in both SH games and GOC. We run regressions with the increase in the

[30] The modest shifts in gaze patterns observed in cooperative players are not statistically different from the ones of L2 players (Table S3.2 (interaction effects), section 7.3 of the Appendices).

proportion of equilibrium response (Phase 3 – Phase 1) in each of the four classes of game as dependent variables, and the decrease in L2 distance (Phase 1 – Phase 3) as independent variable (Table S3.3 in section 7.3, Appendices). Results show that the decrease in L2 distance predicts the increase in the proportion of equilibrium responses in DSO games in L1 players ($B = 0.61$, $p < .001$). This effect leads to a modest average increase (16 %) in equilibrium responses in DSO games for the L1 group ($B = 0.64$, $p = .052$).[31] DSO games are crucial since an equilibrium can be found only by predicting the counterpart's move and best responding to this expectation. We do not find any other significant effect of phase on the proportion of equilibrium or risk-dominant choices across groups and classes of games (Table S3.3, section 7.3 of the Appendices). In Table 2.2, we report the proportion of equilibrium responses in each class of game in Phase 1 and Phase 3.

Group (Phase 1)	N	Proportion of equilibrium responses							
		Phase 1				Phase 3			
		DSS	DSO	SH	GOC	DSS	DSO	SH	GOC
Level-1	19	0.85 (0.16)	0.31 (0.23)	0.77 (0.24)	0.68 (0.26)	0.85 (0.14)	0.47 (0.31)	0.73 (0.30)	0.73 (0.33)
Level-2	35	0.87 (0.13)	0.69 (0.21)	0.69 (0.30)	0.64 (0.27)	0.90 (0.15)	0.74 (0.27)	0.69 (0.38)	0.64 (0.31)
Cooperative	41	0.66 (0.21)	0.57 (0.15)	0.38 (0.31)	0.74 (0.31)	0.73 (0.23)	0.54 (0.22)	0.43 (0.41)	0.77 (0.33)

Table 2.2. Proportion of equilibrium responses (risk dominant equilibrium for SH and GOC games) organized by Group, Phase and Game. Standard deviations in parentheses.

[31] Random effects linear regression with errors clustered by subject (robust errors). The proportion of equilibrium responses is the dependent variable, dummies for group and phase as independent variables.

4.4 Discussion

In an eye-tracking experiment, we investigate if unsophisticated types of players change their patterns of information acquisition and choices after they experience alternative decision rules. Results show that the visual analysis of level-1 players shifts towards the one predicted by the level-2 strategy after the exposure to alternative decision rules, including level-2 play. This effect is driven by an increase in the proportion of other's payoff transitions, suggesting that the attentional shift is directed towards the evaluation of the incentives of the counterpart to form beliefs about her preferred action. These findings indicate that level-1 players, if exposed to more sophisticated strategies, do realize that they should consider more thoughtfully the incentives of the counterpart. Our results are in line with the hypothesis that unsophisticated behavior is associated with a non-exhaustive representation of the game structure (Devetag & Warglien 2008) or the action space of the players involved in the interaction (Verbrugge et al. 2018). Moreover, the observed attentional shift predicts a selective increase in the rate of equilibrium responses in games in which the counterpart has a dominant action, suggesting that the other-oriented change in gaze patterns has an impact on choices in relevant games. These results are consistent with recent findings (Verbrugge et al. 2018) showing that players can increase their level of strategic thinking after step-by-step training and instructions about the existence of different levels of reasoning in games. Nevertheless, we acknowledge that the average shift in choices for L1 players is rather modest, which can be explained in several ways. On the one hand, it is possible that the simple exposure to alternative models of choice, without any information about their efficacy, is not sufficient for a robust increase in strategic sophistication. On the other hand, we can hypothesize that the increase in the attention towards other's incentives does not necessarily translate into a comparable increase in strategic thinking. This interpretation is in line with recent results (Polonio & Coricelli 2019) showing that level-1 players choose the level-1 action even if they believe that their counterpart has a preferred action.

Moreover, our results show that cooperative players do not change their patterns of visual analysis and continue to focus on intra-cell comparisons and play cooperatively after exposure to alternative rules. These results suggest that the visual analysis and behavioral strategy of these players are motivated by the desire to achieve the social optimum, even if they are aware of the steps of strategic reasoning that are necessary for maximizing their personal payoff. This indicates that the behavior of cooperative players is driven by other-regarding preferences, as suggested by recent studies (Devetag et al. 2016; Polonio et al. 2015), highlighting how theories of social preferences can capture behavior of a substantial segment of players in one-shot games. Altogether, our results provide novel evidence about the cognitive drivers and the stability of attentional patterns and behavioral strategies in games, and shed new light on theories of bounded rationality and on theories of social preferences.

5. Concluding discussion

In three eye-tracking studies, we have shown that we can use eye-tracking to disclose processes of spontaneous strategy generation in judgment and decision making settings. We have also reported results suggesting that the emergence of unsophisticated information-processing strategies is not associated with cognitive abilities such as working memory and fluid intelligence, but rather on a measure of cognitive style such as cognitive reflection. In line with these correlational results, we also provided evidence showing that the attentional mechanisms sustaining the generation and implementation of unsophisticated strategies can be reconsidered and updated under the impact of endogenous and exogenous cues revealing the existence of alternative information-processing behaviors.

Results of Study 1 revealed the existence of two strategies in the generation of relational representation of hypothetical interdependent states. We disclosed this heterogeneity by analyzing participants' eye movements in a novel Relational Inference task, which aimed to unravel whether participants were spontaneously building either sophisticated or unsophisticated internal models of the relational environment. Results showed that some (sophisticated) agents built relationally explicit models interrelated events, while other (unsophisticated) agents built unstructured relational models without grasping the underlying relational complexity. The emergence of heterogeneity in attentional behavior was predicted by cognitive reflection and not by fluid intelligence and working memory. Interestingly, most of the unsophisticated participants changed gaze patterns and encoding strategy in a second repetition of the task, after having received additional information about the existence of two strategies and their respective efficiencies. This attentional and behavioral shift, together with correlational results linking strategy generation to cognitive reflection, indicates that some individuals are less prone to spontaneously build relationally-rich models of the environment, although they are able and motivated to switch strategy as soon as they realize that their behavior is not effective (see Kahneman, 2003) . Moreover, we reported results showing that variability in information-processing similarly emerges in conditional reasoning with verbal conditional sequences expressing real life hypothetical scenarios, suggesting the existence of general and context-independent mechanisms of spontaneous information-processing strategy generation in reasoning.

In two additional studies, we explored processes of strategy generation in social interactive scenarios, where outcomes of decisions can be influenced by others' actions. Results of Study 2 reveal that individual levels of cognitive reflection explain the emergence of different information-processing strategies in normal-form games. In particular, high cognitive reflection predicts the ability to integrate others' incentives in the internal representation of the game environment, which in turn allows the generation of predictions about others' potential actions and, therefore, the implementation of strategic behavior. In study 3, we have reported results shading light on the mechanisms of stability and adaptation of gaze patterns and behavioral strategies in strategic interaction. In particular, we have shown that unsophisticated players, who generally do not consider others' incentives, shift attentional patterns after being exposed to alternative decision models that do consider the behavior of the counterpart. More specifically, they start to consider others' payoff and integrate them in their model of the interactive decision problem, and this attentional shift predicts an increase in the proportion of strategic choices in relevant games.

Taken together, the experimental work reported in this thesis provides novel evidence about the process of generation of information-processing strategies in judgment and decision making. Early endogenous patterns of information search have been shown to robustly predict behavior in both interactive and non-interactive decision settings, highlighting the crucial role of information-processing in complex cognition. We found a robust correlation between early patterns of information acquisition and individual cognitive reflection levels in both individual and interactive decision contexts, but we did not show results indicating a crucial role of cognitive capacity measures such as fluid intelligence and working memory in the emergence of these distinct attentional patterns. High cognitive reflection levels seem to reflect a preferential access to more deliberative processes of information search, manipulation and representation (Osman, 2004), which in turn modulate the generation of more sophisticated strategies in task resolution. This interpretation is coherent with the idea that the ability to construct more sophisticated internal models of the decision or judgment problem represents a more malleable thinking disposition, rather than an unmodifiable cognitive ability (see for example Campitelli & Labollita, 2010, Toplak & Stanovich, 2002). More precisely, the CRT score captures the individual propensity to instantiate more or less deliberative and thoughtful processing, which in turn modulates the probability of instantiating more or less sophisticated processing in a given setting. This individual tendency may be associated with the need to balance a trade-off between cognitive cost and effectiveness of the selected strategy and might be therefore linked to meta-cognitive factors sustaining the evaluation of performance of the current strategies and alternative ones. This hypothesis indeed suggests that, in presence of informative cues about the existence of alternative (better) strategies, agents may re-evaluate the current (unsophisticated) strategy in favor to more sophisticated ones. In line with this hypothesis, results of Study 1 and Study 2 indicate that unsophisticated information-processing behavior can be overcome by endogenous and exogenous signals providing implicit or explicit information about the efficiency of current and alternative strategies. In particular, factors such as feedback, additional instructions or simple practice can trigger more deliberative and analytical processing, leading to the exploration and implementation of new behavioral strategies (see Ball, 2013b; Evans, 1984, 2006).

Study 2 and 3 confirm that exploring attentional mechanisms of search, manipulation and representation of task-relevant information is fundamental also in interactive contexts, where the presence of other intelligent agents has an influence on the outcomes of our choices. By using normal-form games, we modelled own and others' incentives in terms of monetary expected gains and we used eye-tracking to investigate whether and how our participants incorporated others' incentives in their decision models. Our results confirm recent experimental findings (Brocas et al. 2014, 2018; Costa-Gomes et al. 2001; Devetag et al. 2016; Hristova & Grinberg 2005; Polonio et al. 2015; Polonio

& Coricelli 2018) showing that gaze pattern can robustly predict strategic sophistication and choices in one-shot games. For instance, disregarding relevant comparisons between the payoffs of the counterpart generally leads to unsophisticated choices reflecting strategic thinking of level-1 in hierarchical theories of strategic thinking like Cognitive Hierarchy and Level-K. Interestingly, results of Experiment 2 show that deviations from the expected visual patterns of information acquisition are associated with individual levels of cognitive reflection. Specifically, unreflective agents tend to disregard those payoff comparisons that are necessary to form beliefs about the action of the counterpart and therefore engage in strategic recursive reasoning. Individual cognitive style therefore modulates attentional mechanisms sub-serving one of the core components of mentalizing, namely the ability to understand others' preferences (Bilancini et al., 2018). However, results of Study 3 reveal that exposing these participants to other strategies that do take into account the potential actions of the counterpart (i.e. level-2 and cooperative strategies), even without any clue about the efficiencies of these models of choice, leads them to evaluate others' incentives in a more strategic and sophisticated fashion. This suggests that the implementation of the level-1 strategy is associated, at least in the majority of participants, with a poor game representation, rather than with motivational and belief-related factors. These results corroborate previous works suggesting that non-strategic behavior may arise because of game misrepresentation (Devetag et al., 2008), which is in turn associated with the tendency to implement either deliberative or intuitive information processing, as reflected by individual cognitive reflection levels. Our results also demonstrate that sophistication in gaze behavior and strategic thinking in games may increase when players have access to the recursive reasoning mechanisms that are necessary to implement strategic thinking (Verbrugge et al., 2018). These findings therefore confirm that mechanisms of spontaneous strategy generation are crucial in explaining heterogeneity in individual as well as interactive contexts. Nonetheless, results from Study 3 show that players exhibiting visual analysis and choices consistent with cooperative behavior (Devetag et al, 2016; Polonio et al. 2015; Polonio & Coricelli 2018) do not shift gaze patterns after being exposed to level-2 choices, suggesting that they are indeed driven by pro-social motives. Further research is needed to investigate the interaction between mechanisms of information processing and representation and social preferences, in order to have a more exhaustive picture on the drivers of behavior in strategic interaction.

In sum, in this thesis we provided evidence showing how endogenous attentional mechanisms of information search and representation can explain and predict strategy generation processes in individual and interactive tasks. Since we believe these processes to be 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 information-processing mechanisms in explaining the heterogeneity underlying higher cognition.

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7. Appendices

7.1 Study 1

7.1.1 Experiment 1

Relational-inference task: 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 (Figure S1.1); 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.

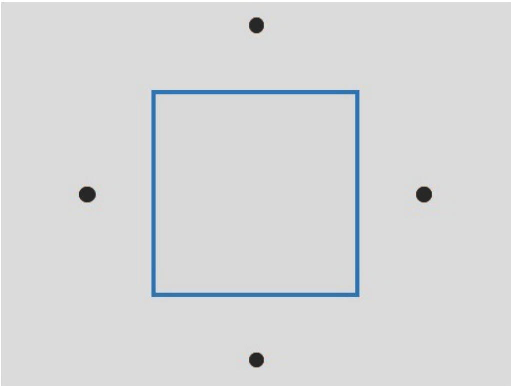


Figure S1.1. Possible positions of the fixation point (in black) that preceded the Representation phase of the Relational-inference task (randomized across trials). The blue square indicates the area that included stimuli in the Representation phase.

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.

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 S1.2); 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).

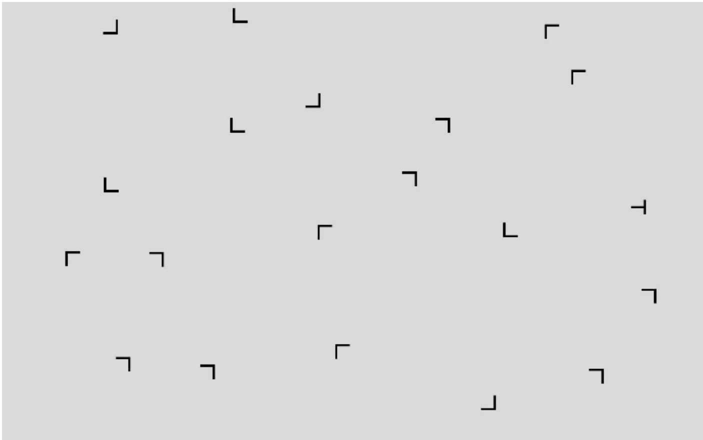


Figure S1.2. Example of the visual search task (target (T) present).

Relational Inference task: additional results

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 S1.1. 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 S1.2. 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 S1.3. 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 S1.4. Stepwise backward regression analysis of group (sophisticated or unsophisticated). 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. Measures excluded from the model: APM, p=0.56; digit span forward, p=0.22; digit span backward, p=0.21; 2-back & 3-back, p=0.3784.

Relational Inference task: 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 S1.5. 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 S1.6. 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 S1.7. 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 CRT and overall accuracy.

Visual search control task: additional results

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 (0.06)	2.02 (0.48)	1.43 (0.26)	5.44 (0.39)
Unsophisticated	25	0.90 (0.07)	2.00 (0.45)	1.42 (0.24)	5.39 (0.38)
TOTAL	50	0.91 (0.07)	2.01 (0.46)	1.43 (0.25)	5.42 (0.38)

Table S1.8. 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).

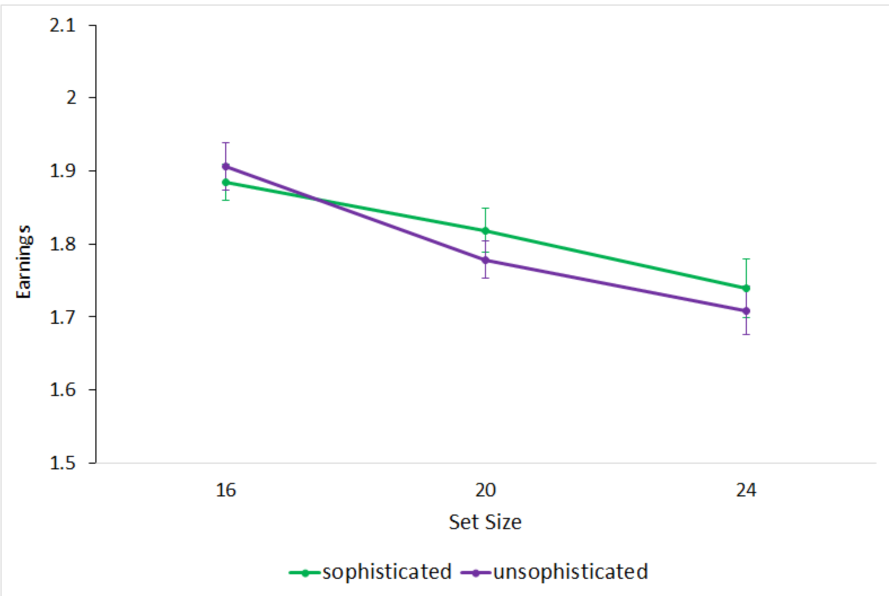


Figure S1.3. Average earnings of sophisticated and unsophisticated groups by set size.

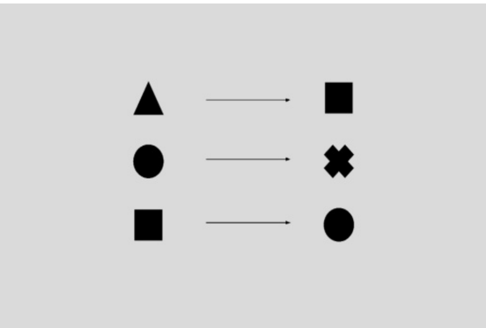
7.1.2. Experiment 2

Additional instructions post-treatment session

The following is a translation of the original instructions of the post-treatment session of Experiment 2 (Study 1), where participants were told about the existence of the sophisticated and the unsophisticated strategy in the Relational-inference task and their respective average efficiencies.

Instructions:

This experiment has been already administered to a pool of participants in a previous experimental session. We analyzed aye-movements and performance in the task, and we discovered that there are two common ways of performing the task. These two strategies emerge in the first phase of the trial, when you can see, for 9 seconds, conditional relations between symbols:



Now I will describe to you the two strategies and I will tell you which of the two has been the more effective in the task. Listen to the description of the strategies carefully, independently of the strategy you used in the previous session.

Strategy 1

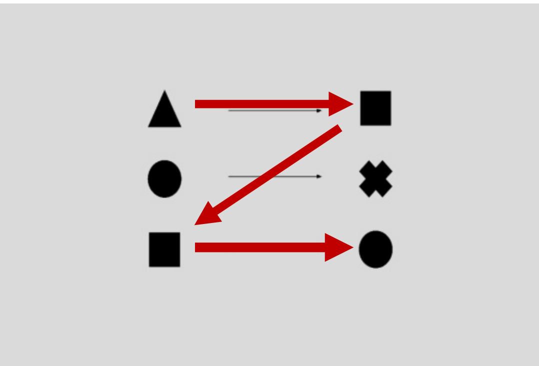
Strategy n.1 consists in the simple memorization of the three conditional rules in the order they are presented, from top to bottom. The pairs of symbols are memorized and kept in mind until the source state (e.g. square). After the disclosure of the source state, the strategy is to make an inference after the other starting from the source state (e.g. from square to circle, from circle to cross, in the example above).

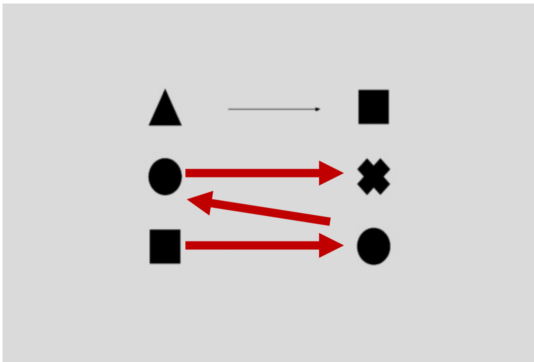
This strategy has been shown to be quite ineffective: participants that used this strategy gained on average 5.58 euros (62% of correct responses).

Strategy 2

Participants using Strategy n.2, in the phase of encoding of symbols, first try to look for the transitive relations between conditional pairs of symbols, to detect triplets of sequential events.

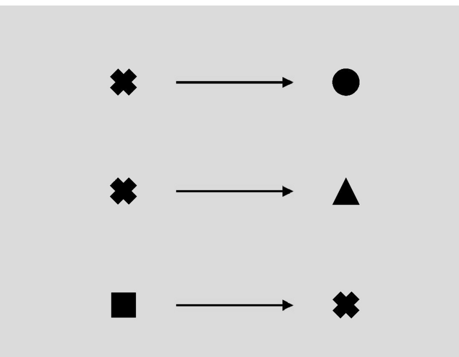
In the above example, they used some seconds to detect two triplets based on transitive relations: triangle-square-circle and square-circle-cross:



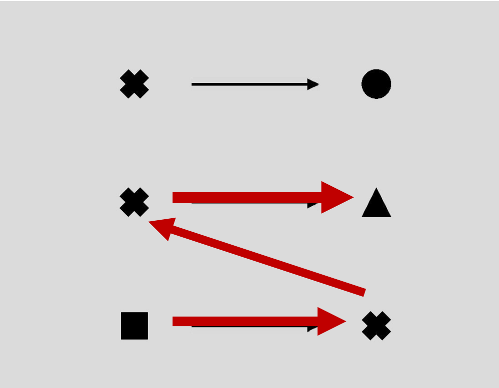


Once these relations were detected, they combined them in a single sequential chain (triangle-square-circle-cross) and they memorized it. After the disclosure of the source state (e.g. square) they selected all the symbols that followed in the sequential chain they built in their mind (e.g. circle, cross)

In other types of trial, like:

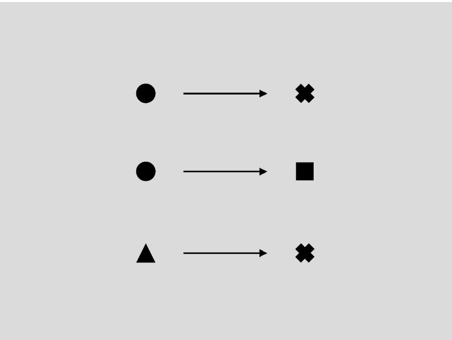


They first looked for potential transitive relations between conditionals



After they have detected the sequential triplet square-cross-triangle, they noticed that "cross" had another consequence (circle). Eventually, they combined these relations in a unique sequence of the type square-cross-(triangle & circle).

Finally, in trials like:



After having noticed that there are no transitive relations between symbols, they tries to memorize symbols in a unique integrated model, taking advantage of the repetition of symbols. For example, they memorized a sequence like: circle-(cross & square)-triangle-cross.

This strategy has been more effective that strategy n.1: participants who used it gained on average 7.56 euros (84% of correct responses).

These two strategies were described to you just for your information. Now we ask you to perform again the task in the way you prefer, even using a strategy different from the ones we have described.

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 S1.9. 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 S1.10. 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).

7.1.3. Experiment 3

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 S1.11. 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 S1.12. Multivariate regression with accuracy in each type of inference as dependent variables and Backward digit-span as independent variable. One subject excluded from analysis (backward digit span score not collected).

7.2. Study 2

7.2.1. Experiment 1

Additional methods: procedure of cognitive tests

Cognitive Reflection Test: Participants answered the three questions of the CRT without any time limit. The number of correct responses in the test represents the *CRT score*.

Raven Advanced Progressive Matrices Test (APM): Participants performed a 20-minute timed version of the test. We utilized a 20-minutes timed version of the APM test since previous studies have shown that it is an adequate predictor of the untimed APM score (Hamel & Schmittmann, 2006). Participants were incentivized by receiving 20 cents for each correct response (maximum 7.20 euros). We refer to *Raven score* as the number of correct responses in the test.

Forward digit span: Participants were asked to repeat orally a series of digits in the order they were presented. Number of digits increased until participants made two mistakes. The length of last series recalled correctly by a participant reflected her *forward digit span*.

Backward digit span: We asked participants to repeat in reverse order a series of digits. Similarly to the forward digit span, digit sequences increased in length until participants made two mistakes, and the number of digits of the last series recalled correctly by a participant reflected her *forward digit span*.

N-back task: Participants observed series of single letters appearing at the center of the screen for 1000 ms, followed by a blank screen (1000 ms) anticipating the appearance of the next letter. The task consisted of two blocks of 100 trials each. In the first block, participants had to decide if the letter in the current trial matched the one observed two trials before (2-back). In the second block, they had to decide whether the current letter matched the one observed three trials before (3-back). Participants implemented their decision by pressing a button for “match” or pressing nothing for “non-match”. Participants were paid according to the proportion of correct responses (min 1 euro, max 6 euros). We refer to *n-back score* as the proportion of corrected responses in the task.

DSS games

Game 1

	i	ii
I	$\underline{4,4}$	6,3
II	3,3	5,5

Game 2

	i	ii
I	4,4	6,6
II	$\underline{5,5}$	7,4

Game 3

	i	ii
I	8,5	$\underline{6,6}$
II	7,7	5,5

Game 4

	i	ii
I	8,8	6,6
II	9,6	$\underline{7,7}$

Game 5

	i	ii
I	5,5	3,3
II	6,3	$\underline{4,4}$

Game 6

	i	ii
I	7,4	$\underline{5,5}$
II	6,6	4,4

Game 7

	i	ii
I	$\underline{6,6}$	8,5
II	5,5	7,7

Game 8

	i	ii
I	6,6	8,8
II	$\underline{7,7}$	9,6

Game 9

	i	ii
I	1,5	5,3
II	2,3	$\underline{6,4}$

Game 10

	i	ii
I	3,4	$\underline{7,5}$
II	2,6	6,4

Game 11

	i	ii
I	7,5	3,7
II	$\underline{8,6}$	4,5

Game 12

	i	ii
I	$\underline{9,7}$	5,6
II	8,6	4,8

Game 13

	i	ii
I	$\underline{6,4}$	2,3
II	5,3	1,5

Game 14

	i	ii
I	6,4	2,6
II	$\underline{7,5}$	3,4

Game 15

	i	ii
I	3,7	7,5
II	4,5	$\underline{8,6}$

Game 16

	i	ii
I	5,6	$\underline{9,7}$
II	4,8	8,6

DSO games

Game 17

	i	ii
I	3,3	$\underline{4,4}$
II	5,5	3,6

Game 18

	i	ii
I	$\underline{5,5}$	4,4
II	4,7	6,6

Game 19

	i	ii
I	7,7	5,8
II	5,5	$\underline{6,6}$

Game 20

	i	ii
I	6,9	8,8
II	$\underline{7,7}$	6,6

Game 21

	i	ii
I	3,6	5,5
II	$\underline{4,4}$	3,3

Game 22

	i	ii
I	6,6	4,7
II	4,4	$\underline{5,5}$

Game 23

	i	ii
I	5,5	$\underline{6,6}$
II	7,7	5,8

Game 24

	i	ii
I	$\underline{7,7}$	6,6
II	6,9	8,8

Game 25

	i	ii
I	3,5	$\underline{4,6}$
II	5,1	3,2

Game 26

	i	ii
I	$\underline{5,7}$	4,6
II	4,3	6,2

Game 27

	i	ii
I	7,3	5,4
II	5,7	$\underline{6,8}$

Game 28

	i	ii
I	6,5	8,4
II	$\underline{7,9}$	6,8

Game 29

	i	ii
I	3,2	5,1
II	$\underline{4,6}$	3,5

Game 30

	i	ii
I	6,2	4,3
II	4,6	$\underline{5,7}$

Game 31

	i	ii
I	5,7	$\underline{6,8}$
II	7,3	5,4

Game 32

	i	ii
I	$\underline{7,9}$	6,8
II	6,5	8,4

Figure S2.1. Full list of 2x2 games. The line in one of the cells of each matrix signals the equilibrium solution of the game.

Additional results

Proportion of equilibrium responses	B	SE	t	p	95 % CI	
CRT score	0.18	0.15	1.22	.230	-0.12	0.47
N. obs.	48					

Table S2.1. Linear regression of proportion of equilibrium response in DSS games. CRT score is the independent variable.

Proportion of equilibrium responses	B	SE	t	p	95 % CI	
CRT = 1	0.64	0.41	1.56	.127	- 0.19	1.47
CRT = 2	0.59	0.38	1.58	.122	- 0.17	1.35
CRT = 3	0.45	0.41	1.10	.278	-0.38	1.28
N. obs.	48					

Table S2.2. Linear regression of proportion of equilibrium response in DSS games and CRT score as group factor.

Strategic IQ	B	SE	z	p	95 % CI	
CRT = 1	0.42	0.40	1.10	.276	- 0.35	1.18
CRT = 2	0.06	0.35	0.18	.854	- 0.63	0.76
CRT = 3	1.19	0.38	3.14	.003	0.43	1.96
N. obs.	48					

Table S2.3. Linear regression of Strategic IQ in DSO games. CRT score as group factor.

Transition type	CRT	Raven	Forward span	Backward span	N-back
Own-payoffs within-action	.492	.336	.765	.515	.384
Own-payoffs between-action	.988	.533	.365	.221	.737
Other-payoffs within-action	**.001**	.706	.283	.117	.384
Other-payoffs between-action	.930	.882	.998	.509	.751
Intra-cell	.810	.931	.228	.406	.814
N. obs.	48	48	48	48	48

Table S2.4. Results of stepwise backward regressions. We report the p.values of the effects of cognitive measures on the average proportion of the five types of relevant transitions. The only significant effect is the one of CRT score on the average proportion of other-payoffs within-action transitions.

Proportion of equilibrium responses	B	SE	t	p	95 % CI	
Prop. other-payoffs within-action transitions	0.09	0.03	2.91	.006	0.03	0.16
CRT score	0.03	0.03	0.95	.348	-0.03	0.09
N. obs.	48					

Table S2.5. Linear regression of proportion of equilibrium responses in DSO games with other-payoffs within-action transitions and CRT score as independent variables. Introducing other-payoffs within-action transitions as independent variable, the effect of CRT = 3 (observed in Table 5) is no longer significant, indicating full mediation of other-payoffs within-action transitions on the relationship between CRT score and proportion of equilibrium responses.

Proportion of equilibrium responses	B	SE	t	p	95 % CI	
Prop. other-payoffs within-action transitions	0.38	0.14	2.60	.013	0.08	0.67
CRT = 1	0.25	0.37	0.68	.502	- 0.49	0.99
CRT = 2	-0.12	0.34	-0.35	.725	- 0.81	0.56
CRT = 3	0.66	0.41	1.60	.116	-0.65	1.48
N. obs.	48					

Table S2.6. Linear regression of proportion of equilibrium responses in DSO games with other-payoffs within-action transitions and CRT score (categorical) as independent variables. Introducing other-payoffs within-action transitions as independent variable, the effect of CRT = 3 (observed in Table 6) is no longer significant, indicating full mediation of other-payoffs within-action transitions in the relationship between CRT score and strategic choices.

7.2.2. Experiment 2

Additional methods

Game 1	i	ii	iii
I	78,73	69,23	12,14
II	67,52	59,61	78,53
III	16,76	65,87	94,79

Game 2	i	ii	iii
I	21,67	59,57	85,63
II	71,76	50,65	74,14
III	12,10	51,76	77,92

Game 3	i	ii	iii
I	74,38	78,71	46,43
II	96,12	10,89	57,25
III	15,51	83,18	69,62

Game 4	i	ii	iii
I	73,80	20,85	91,12
II	45,48	64,71	27,59
III	40,76	53,17	14,98

Game 5	i	ii	iii
I	78,49	60,68	27,35
II	10,82	49,10	98,38
III	69,64	42,39	85,56

Game 6	i	ii	iii
I	39,99	36,28	57,86
II	83,11	50,79	65,70
III	11,50	69,61	40,43

Game 7	i	ii	iii
I	84, 82	33, 95	12, 73
II	21, 28	39, 37	68, 64
III	70, 39	31, 48	59, 81

Game 8	i	ii	iii
I	47, 30	94, 32	36, 38
II	38, 69	81, 83	27, 20
III	80, 58	72, 11	63, 67

Game 9	i	ii	iii
I	57, 58	46, 34	74, 70
II	89, 32	31, 83	12, 41
III	41, 94	16, 37	53, 23

Game 10	i	ii	iii
I	60, 59	34, 91	96, 43
II	36, 48	85, 33	39, 18
III	72, 76	43, 14	25, 55

Game 11	i	ii	iii
I	43, 91	38, 81	92, 64
II	39, 27	79, 68	68, 19
III	69, 10	66, 21	74, 54

Game 12	i	ii	iii
I	25,27	90, 43	38, 60
II	49, 39	53, 73	78, 52
III	64, 85	20, 46	19,78

Game 13	i	ii	iii
I	83, 40	23, 68	70, 81
II	93, 45	12, 71	29, 41
III	66, 94	56, 76	21, 70

Game 14	i	ii	iii
I	82, 61	36, 46	24, 22
II	43, 17	70, 50	40, 87
III	75, 16	49, 75	57, 35

Figure S2.2. List of 3x3 games. The underlined payoffs indicate the pure-strategy Nash equilibria. Games 1, 3, 5, 7 are solvable with 2 steps of iterated dominance (row player). Games 2, 4, 6, 8, 9 are solvable with 3 steps of iterated dominance. Game 10 can be solved with 4 steps of iterated dominance. Games 11, 12, 13, 14 have a unique Nash solution without dominant strategies. The line in one of the cells of each matrix signals the equilibrium solution of the game.

Additional results

Proportion of equilibrium responses	B	SE	t	p	95 % CI	
CRT score	0.16	0.15	1.07	.290	-0.14	0.45
N. obs.	48					

Table S2.7. Linear regression of proportion of equilibrium responses, with CRT score as continuous independent variable.

Strategic IQ	B	SE	z	p	95 % CI	
CRT = 1	0.29	0.43	0.68	.499	- 0.57	1.16
CRT = 2	0.06	0.45	0.14	.886	- 0.83	0.96
CRT = 3	0.52	0.36	1.43	.161	- 0.21	1.25
N. obs.	48					

Table S2.8. Linear regression of Strategic IQ in 3x3 games with CRT score as group factor. $F(3, 44) = 3.96$, $p = .014$, $R^2 = 0.21$.

Equilibrium response	B	SE	Z	p	95 % CI	
Own-payoffs within-action	- 0.19	0.16	- 1.17	.241	- 0.50	0.13
Own-payoffs between-action	0.09	0.09	1.01	.310	- 0.09	0.28
Other-payoffs within-action	- 0.03	0.12	-0.25	.799	- 0.26	0.20
Other-payoffs between-action	0.11	0.09	- 1.13	.260	- 0.08	0.29
Intra-cell	- 0.04	0.14	-0.26	.797	- 0.32	0.24
N. obs.	670					
N. independent obs.	48					

Table S2.9. Mixed-effects logistic model with subject as random effect, equilibrium response as dependent variable and the five types of relevant transitions as independent variables.

Proportion of L2 choices	B	SE	t	p	95 % CI	
Other-payoffs within-action transitions	0.75	0.09	8.05	< .001	0.57	0.94
CRT score	0.13	0.09	1.40	.168	-0.06	0.32
N. obs.	48					

Table S2.10. Linear regression of L2 response. The proportion of other-payoffs within-action transitions and the CRT score are the independent variables. Introducing other-payoffs within-action transitions as independent variable, the effect of CRT (Table 2) is no longer significant. This indicates full mediation of the proportion of other-payoffs within-action transitions on the relationship between CRT score and strategic choices.

Proportion of L2 choices	B	SE	t	p	95 % CI	
Other-payoffs within-action transitions	0.75	0.10	7.81	< .001	0.56	0.94
CRT = 1	0.19	0.26	0.72	.477	- 0.34	0.72
CRT = 2	0.13	0.27	0.49	.624	- 0.42	0.68
CRT = 3	0.35	0.24	1.47	.150	- 0.13	0.83
N. obs.	48					

Table S2.11. Linear regression of proportion of L2 choices with proportion of other-payoffs within-action transitions and CRT score (group factor) as independent variables. The effect of CRT = 3 (Table 3) is no longer significant after the introduction of the proportion of other-payoffs within-action transitions as independent variable, indicating that other-payoffs within-action transitions fully mediate the relationship between CRT score and strategic choices

7.3. Study 3

Additional methods

DSS games

	Game 1 i	Game 1 ii	Game 2 i	Game 2 ii	Game 3 i	Game 3 ii	Game 4 i	Game 4 ii	Game 5 i	Game 5 ii	Game 6 i	Game 6 ii	Game 7 i	Game 7 ii	Game 8 i	Game 8 ii
I	4,4	6,3	4,4	6,6	8,5	6,6	8,8	6,6	5,5	3,3	7,4	5,5	6,6	8,5	6,6	8,8
II	3,3	5,5	5,5	7,4	7,7	5,5	9,6	7,7	6,3	4,4	6,6	4,4	5,5	7,7	7,7	9,6

	Game 9 i	Game 9 ii	Game 10 i	Game 10 ii	Game 11 i	Game 11 ii	Game 12 i	Game 12 ii	Game 13 i	Game 13 ii	Game 14 i	Game 14 ii	Game 15 i	Game 15 ii	Game 16 i	Game 16 ii
I	1,5	5,3	3,4	7,5	7,5	3,7	9,7	5,6	6,4	2,3	6,4	2,6	3,7	7,5	5,6	9,7
II	2,3	6,4	2,6	6,4	8,6	4,5	8,6	4,8	5,3	1,5	7,5	3,4	4,5	8,6	4,8	8,6

DSO games

	Game 17 i	Game 17 ii	Game 18 i	Game 18 ii	Game 19 i	Game 19 ii	Game 20 i	Game 20 ii	Game 21 i	Game 21 ii	Game 22 i	Game 22 ii	Game 23 i	Game 23 ii	Game 24 i	Game 24 ii
I	3,3	4,4	5,5	4,4	7,7	5,8	6,9	8,8	3,6	5,5	6,6	4,7	5,5	6,6	7,7	6,6
II	5,5	3,6	4,7	6,6	5,5	6,6	7,7	6,6	4,4	3,3	4,4	5,5	7,7	5,8	6,9	8,8

	Game 25 i	Game 25 ii	Game 26 i	Game 26 ii	Game 27 i	Game 27 ii	Game 28 i	Game 28 ii	Game 29 i	Game 29 ii	Game 30 i	Game 30 ii	Game 31 i	Game 31 ii	Game 32 i	Game 32 ii
I	3,5	4,6	5,7	4,6	7,3	5,4	6,5	8,4	3,2	5,1	6,2	4,3	5,7	6,8	7,9	6,8
II	5,1	3,2	4,3	6,2	5,7	6,8	7,9	6,8	4,6	3,5	4,6	5,7	7,3	5,4	6,5	8,4

Games with multiple equilibria

Stag Hunt

	Game 33 i	Game 33 ii	Game 34 i	Game 34 ii	Game 35 i	Game 35 ii	Game 36 i	Game 36 ii	Game 37 i	Game 37 ii	Game 38 i	Game 38 ii	Game 39 i	Game 39 ii	Game 40 i	Game 40 ii
I	4,1	5,5	2,5	7,7	6,3	7,7	4,7	9,9	6,6	1,4	7,7	2,5	7,7	6,3	8,8	7,4
II	6,6	1,4	6,6	5,2	8,8	3,6	8,8	7,4	4,1	5,5	5,2	6,6	3,6	8,8	4,7	9,9

Game of Chicken

	Game 41 i	Game 41 ii	Game 42 i	Game 42 ii	Game 43 i	Game 43 ii	Game 44 i	Game 44 ii	Game 45 i	Game 45 ii	Game 46 i	Game 46 ii	Game 47 i	Game 47 ii	Game 48 i	Game 48 ii
I	5,3	1,1	5,5	4,6	7,5	3,3	7,7	6,8	3,5	4,4	5,5	4,6	7,5	3,3	4,4	8,6
II	4,4	3,5	6,4	2,2	6,6	5,7	8,6	4,4	1,1	5,3	6,4	2,2	6,6	5,7	6,8	7,7

Figure S3.1. Complete list of game used in the experiment.

Eye-tracking procedure

Participants are seated in a chair with a soft head restraint to ensure a viewing distance of 55 cm. from 1920 x 1080 resolution monitor. Stimuli are presented through a custom-made program implemented using Matlab Psychtoolbox. Eye movements are monitored and recorded using a tower mounted Eyelink 2000 system (SR. Research Ontario Canada) with a sampling rate of 2000 Hz.

We use a 13-points calibration in which points are placed in correspondence of the eight payoffs, the four corners of the screen and the center. After the calibration phase, a validation phase is run to ensure accuracy of the calibration. The position of points in the validation phase is identical to the one in the calibration phase. Calibration and validation procedures are re-performed in case these are unsuccessful. Before each trial, we perform a drift correction to ensure that participants do stare at the current fixation point; after 300 milliseconds of fixation in the correct location, stimuli are displayed. The payoffs in the game matrix are placed at an optimal distance between each other in to precisely distinguish types of payoff transitions in the eye-tracking analysis.

In line with the gaze analysis performed by Polonio et al. (2015), we define eight regions of interest (ROIs), centered on the matrix payoffs. ROIs have a circular shape with a size of 36000 pixels. The ROIs cover only 23% of the matrix and not overlap. Fixations outside the eight ROIs are discarded. However, although the majority of the screen space is not included in any of the ROIs, most of the fixations (83%) fall inside the ROIs.

Additional results

L2 distance	B	Robust SE	Z	p	95 % CI	
Phase 3 (L2 group)	-0.00	0.12	-0.04	.968	- 0.23	0.22
L1 group (Phase 1)	1.72	0.23	7.51	< .001	1.27	2.17
Cooperative group (Phase 1)	0.99	0.12	8.02	< .001	0.74	1.23
Phase 3 x L1 group	-0.84	0.37	-2.27	.023	-1.56	-0.11
Phase 3 x Cooperative group	0.03	0.16	0.20	.839	- 0.28	0.34
Intercept	-0.69	0.07	-10.34	< .001	-0.82	-0.56
N. obs.	190					
N. independent obs.	95					

Table S3.1. Random effects linear regression with errors clustered by subject. Standard errors are robust. L2 distance is the dependent variable and phase, group and their interactions are the independent variables. Baseline: L2 group in Phase 1.

Proportion of transitions	Own	Other	Intra-cell
Phase 3 (L2 group)	0.03 (0.11)	0.22 (0.13)	0.02 (0.11)
L1 group (Phase 1)	1.53*** (0.22)	-1.59*** (0.17)	-0.67*** (0.11)
Cooperative group (Phase 1)	-0.66** (0.11)	-0.96*** (0.13)	1.20*** (0.12)
Phase 3 x L1 group	-0.80* (0.38)	0.85* (0.40)	0.22 (0.22)
Phase 3 x Cooperative group	0.29 (0.18)	-0.09 (0.17)	-0.31 (0.19)
Intercept	-0.02 (0.08)	0.56*** (0.11)	-0.35* (0.07)
N. obs.	190	190	190
N. independent obs.	95	95	95

*Table S3.2. Random effects linear regressions with errors clustered by subject. Standard errors are robust. Proportion of own, other and intra-cell transitions are the independent variables, and phase, group and their interactions are the independent variables. Baseline: L2 group in Phase 1. We report beta coefficients and robust standard errors (in parentheses). *p < .05; **p < .01; ***p < .001.*

Proportion of equilibrium responses	DSS	DSO	SH	GOC
Effect of Phase (L1 group)	0.00	0.64	-0.11	0.17
	(0.24)	(0.33)	(0.24)	(0.23)
Effect of Phase (L2 group)	0.12	0.22	-0.01	-0.01
	(0.11)	(0.17)	(0.13)	(0.13)
Effect of Phase (Cooperative group)	0.33	-0.12	0.12	0.08
	(0.17)	(0.13)	(0.14)	(0.14)
N. obs.	190	190	190	190
N. independent obs.	95	95	95	95

Table S3.3. Phase effects (linear combination of coefficients) by group resulting from a random effects linear regression (errors clustered by subject, robust standard errors). The proportion of equilibrium responses in DSS, DSO, SH and GOC games are the dependent variables, and phase, group and their interactions are the independent variables. We report the beta coefficient of the linear combinations. Standard errors in parentheses. No effects with $p < .05$.

Instructions and questionnaires (Study 3)

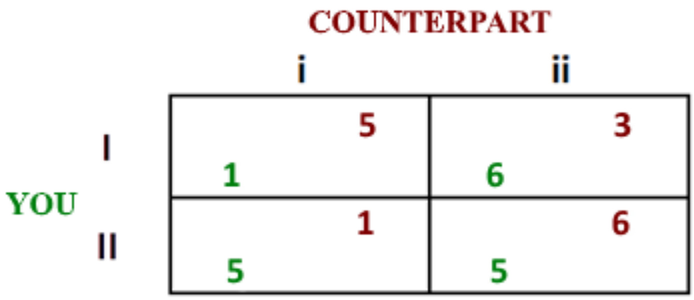
The following is a translation of the original instructions and questionnaires (in Italian).

Instructions Exp. 1

Dear student, you are about to participate in an experiment on interactive decision making. Your privacy is guaranteed; results will be used and published anonymously. Your choices during the experiment will determine your earnings, which you will receive at the end of the data collection, via bank transfer. You can earn between 3 € and 27 €. Your earnings will depend on both your choices and the choices of another participant that will play the same games as you. This participant will receive the same instructions as you, and her/his earnings will depend, as in your case, on the combination between your choices and hers/his.

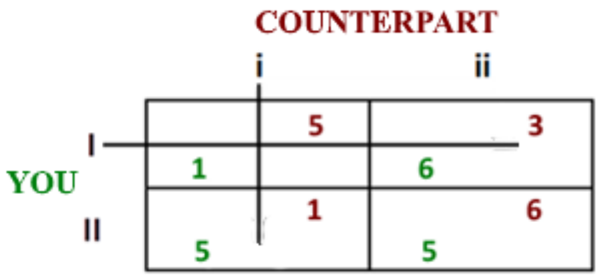
General structure of the game

This part of the experiment consists of 32 rounds. In each round, you will face an interactive decision-making situation. The structure of each interactive decision problem, which we will call "game" henceforth, will be represented by a matrix like the one shown below. Each number in the matrix indicates an amount in euros. Throughout the experiment, you will always play as the row player and you will have to choose either row I or row II, while the other participant (counterpart) will always play as the column player and it will choose either column i or column ii.



From each combination of choices of the **ROW PLAYER** and **COLUMN PLAYER** (i.e., for each combination of rows and columns), one cell of the matrix will be selected. Each cell contains two numerical values (one in green and one in red). These values correspond to a score for each player. In each cell, the number at the bottom and in green represents the score for the ROW PLAYER (yours), while the number on top and in red represents the score for the COLUMN PLAYER (the one of the counterpart).

For example, in the matrix below, if YOU choose row I, and your counterpart chooses column i, your respective scores will be located in the cell at the intersection between the selected row and column.



In this example, the score is 1 for you and 5 for the other player.

Keep in mind that you cannot directly choose the cell of the matrix, but only one of the rows (the counterpart with whom you will be matched will choose one column). Only the combination of both choices will select one and only one cell, corresponding to your earnings and to those of the counterpart.

The choices that you and the other participant will make, and the corresponding results, will not be communicated to you or her/him after each game.

In each of the 32 rounds, the screen will show the decisional matrix for that round, and you will be asked to make a decision. To select your choice, you will have to press key 1 for row I (the row on the top of the matrix) and key 2 for row II (the row on the bottom of the matrix).

You will face 32 decisional matrices, corresponding to 32 different interactive situations. There is no relation between your choices in the different games, each game is independent from the others. You have not time limit in your response.

Payment

Your earnings will be determined at the end of the entire experiment. We will use the following procedure. Each matrix is identified by a code. Some tags will be placed in a box, each showing the code of one of the matrices. The experimenter will ask you to pick three of these tags from the box. You will be paid according to the sum of the earnings obtained in the matrices correspondent to the extracted codes. Specifically, your earnings will be determined by the combination between your choice and the choice of your counterpart, in the games you have drawn. The earning of all other participants will be determined using the same procedure.

Since each of the 32 decisional matrices of the experiment has the same probability of being selected for payment, we ask you to devote the same attention to all of them.

Before the experiment starts, we will ask you to answer a simple questionnaire, in order to test whether instructions have been clearly understood or whether clarifications are needed. If there are incorrect answers, the relevant part of the instructions will be repeated. The experiment will start after the questionnaire phase is completed.

Thank you for your participation!

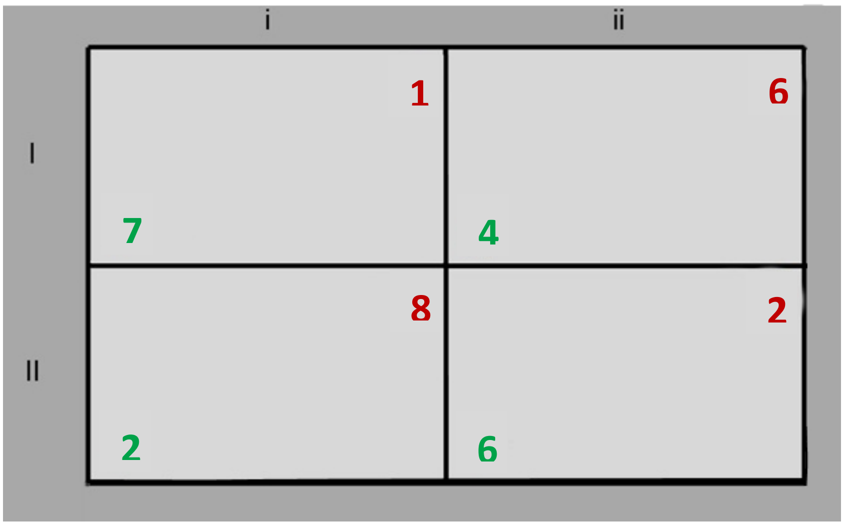
Questionnaire Exp. 1

Dear Participant,

the following questionnaire has the sole purpose of verifying your understanding of the rules of this experiment. We ask you to answer the following questions. If you are uncertain about how to respond, please consult the instructions sheet or the experimenter. Your answers to these questions will not affect your earnings in the experiment.

Thank you for your cooperation!

Considering this game:



Suppose you are assigned the role of ROW PLAYER:

- If the COLUMN PLAYER chooses the first column and you choose the first row, how many EUROs will you earn? .... And how many will the other player earn? ....
- If you choose the second row, and COLUMN PLAYER chooses the first column, how many EUROs will that person earn? .... And how many EUROs will you earn? ....
- If the other player chooses the second column, your earnings will be: …………
- If you choose the first row: ....
- If you choose the second row: ....

Suppose you are assigned the role of COLUMN PLAYER:

- If the ROW PLAYER chooses the first row and you choose the second column, how many EUROs will you earn? .... And how many will the other player earn? ....
- If the other player chooses the second row, your earnings will be: ……
- If you choose the first column: ....
- If you choose the second column: ....

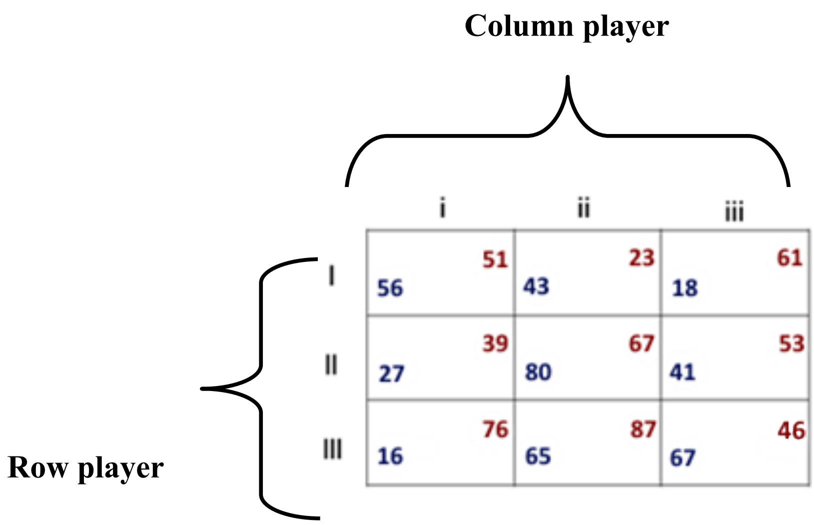
Instructions Exp. 2

Dear student, you are about to participate in an interactive decision making experiment. Your privacy is guaranteed; results will be used and published anonymously. The experiment is divided into two parts. Each part of the experiment will be described in detail below. In total, you can earn between €3.10 and €29.00.

General structure of the game

The task consists of 14 rounds. In each round you will face an interactive decision-making situation. In each round you will have to choose one **of three options**: the word "*interactive*" indicates that the outcome of your decision will be determined by your choice and the choice of another randomly chosen participant.

The structure of each interactive decision problem, henceforth **game**, will be represented by a matrix like the one shown below.



Each number in the matrix indicates an amount in euros (e.g. 56 indicate 5 euros and 60 cents). Throughout the experiment, you and the participant with whom you will be paired will play the roles, respectively, of **ROW PLAYER** and **COLUMN PLAYER**. The available choices of the **ROW PLAYER** (for you) are represented by the **rows** of the matrix (the row on top “**I**”, the row in the middle “**II**” and the row at the bottom “**III**”). The available choices of the **COLUMN PLAYER** are represented by the **columns** of the matrix (the column on the left “**i**”, the column on the center “**ii**” and the column on the right “**iii**”).

Each possible combination of choices of the row and column player (i.e., each possible combination of rows and columns) identifies one cell in the matrix. Each cell reports two numerical values. These values indicate the earnings (in EUROS) of each participant associated with that combination of choices. Conventionally, the blue number on the bottom-left corner of the cell represents the earnings of the **ROW PLAYER** (your earning), while the red number on the top-right corner represents the earnings of the **COLUMN PLAYER**.

For example: in the table below, if **YOU** choose the second row (II) and the **OTHER PLAYER** chooses the first column (i), then your earnings will be those in the cell at the intersection of the selected row and column. In this example, **YOU** earn 2.70 EUROS and the **OTHER PLAYER** 3.90 EUROS.

	i	ii	iii
I	56 51	43 23	18 61
II	27 39	80 67	41 53
III	16 76	65 87	67 46

Bear in mind that you cannot directly choose the cell of the matrix, but only one of the rows (the other participant with whom you will be matched will choose one column). Only the combination of both choices will select one and only one cell.

The choices that you and the other participant will make, and the corresponding results, will not be communicated to you at the end of each period.

You will face 14 matrices, corresponding to 14 different interactive situations. Each game is independent of all other games and there is no time limit on responses. To help you with your choice, the row-player payoffs (your payoffs) will be located in the bottom-left corner of each cell and will be in blue, while the payoffs of the column player (the counterpart) will be located in the top-right corner of the cell and will be in red.

To select your choice you will have to press key 1 for the row I (the row on the top), key 2 for the row II (the row in the middle) and key 3 for the row III (the row on the bottom).

Payment

Your earnings will be determined at the end of the experiment through the following procedure. Each game is identified by a code. Some tags will be placed in a box, each showing the code of one of the matrices. The experimenter will ask you to pick three of these tags from the box. You will be paid according to the sum of earnings obtained in the game corresponding to the extracted codes. Your earnings will be determined by your choices and the choices of the column player that was randomly associated with you, in the games you have drawn. The earning of all other participants will be determined using the same procedure.

Since each of the 14 matrices has the same positive probability of being selected for payment, we ask you to devote the same attention to all of them.

Before the experiment starts, we will ask you to answer a simple anonymous questionnaire, in order to test whether instructions have been clearly understood or whether clarifications are needed. If there are incorrect answers, instructions will be repeated. The first part of the experiment will start after the questionnaire phase is completed.

Questionnaire Exp. 2

Dear Participant,

the following questionnaire has the sole purpose of verifying your understanding of the rules of the choice task. We ask you to answer the following questions. If you are uncertain about how to respond, please consult the instructions sheet. Your answers to these questions will not affect your earnings in the experiment.

Thank you for your cooperation!

	i	ii	iii
I	2 3	4 2	9 1
II	6 4	5 4	6 7
III	3 2	2 1	8 2

<u>Suppose you are assigned to the role of Row Player:</u>

- If the column player chooses the column ii and you choose the row I, how many euros will you earn? ……… and how many will the other player earn? …….
- If you choose the row II and column player chooses the column iii, how many euros will the column player earn? ……… and how may euros will you earn? …….
- If the other player chooses the column i, your earning will be:

    if you choose the row **I**: ……..

    if you choose the row **II**: ……..

    if you choose the row **III**: ……..

<u>Suppose you are assigned to the role of Column Player:</u>

- If the row player chooses the row ii and you choose the column I, how many euros will you earn? ……… and how many will the other player earn? …….
- If the other player chooses the row i, your earning will be:

    if you choose the column **i**: ……..

if you choose the column **ii:** ……..

if you choose the column **iii**: ……..

- Your role (as ROW or COLUMN PLAYER) in the rounds of the experiment will change:

  TRUE or FALSE

- The participant with whom you are paired will be determined randomly in each round, and you will never be matched more than once with the same participant.

  TRUE or FALSE

- After you have taken your decision on a table, you will be able to observe the choice of the participant with whom you were paired.

  TRUE or FALSE