Inquisitiveness: Distributing Rational Thinking

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Abstract

Purpose — This study aims at redefining bounded rationality on the basis of a more socialized view of the individual. In doing so, it introduces inquisitiveness as a key disposition that some team members use to assemble and integrate knowledge when solving problems.

Design/methodology/approach — Using an agent-based computational simulation, this research models different simulated employees working together in ad hoc teams to solve problems.

Findings — Results show that inquisitiveness may work as an efficiency driver that, when present, economizes on knowledge needed by team members to solve problems. In addition to that, results also show that environments with many problems are more suitable for inquisitive individuals to be effective.

Originality/value — Following the late Herbert Simon, the article takes the stance that rationality should be redefined as a socially-oriented process and introduces inquisitiveness as one — although probably not the only one — of the characteristics that help individuals and teams to make rational decisions.

Keywords: inquisitiveness, bounded rationality, agent-based modeling, docility, decision making, problem solving, ad hoc teams, competence, problem difficulty
Inquisitiveness

1 Introduction

This article is an attempt to expand the more traditional view of bounded rationality (BR). The focus of the paper is on problem solving and, in particular, on how team members with a diverse set of social attitudes affect performance. The objective of the article is to re-define BR on a more social ground, using teams to show how rational bounds are recombined and reconfigured to allow problem solving. As recently highlighted (e.g., Fioretti, 2013; Secchi, 2015), agent-based computational simulation are deemed to be an appropriate technique to address this point from a theoretical perspective. In the following pages, we first define the problem, then introduce how some team members bring exploration of cognitive resources and understanding of others to the higher level — something we call inquisitiveness for lack of better words —, present the model and discuss some of its implications.

1.1 Bounded Rationality: Limits of the received view

Simon posited that rationality is always bounded in the sense that a decision is made regardless of all the alternatives that are available (Simon, 1955, 1997). That is due to the intrinsic limitations of the decision-maker’s cognitive system, which can only deal with a narrow subset of the alternatives available in any given situation (March, 1994; Simon, 1997). What “bounded” means, though, heavily depends on the way we interpret this last statement. What Simon seems to have hinted at is that BR might be qualitatively different from any other form of classical or omniscient rationality (e.g., Gilboa, 2010; von Neumann et al., 1944). In other words, it is not just that we can only cope with a modest fraction of the alternatives available. Conversely, it seems that it is the entire “mechanism” of making rational decisions that changes.

It is often assumed that the limitations are working on the means in our decision-making process. That is, the limitations forced upon our rationality by our “intrinsic boundedness” impede us to choose the optimal set of means (Secchi, 2016). Therefore, the selection of means should proceed in different ways, i.e., by making use of heuristics, shortcuts, and all sorts of rules of thumb — our “bag of tricks”. That is very much what the term “bounded” stands for in a more contemporary sense of the word (e.g., Kahneman, 2003; Gigerenzer and Selten, 2001).

At a closer inspection, though, our intrinsic boundedness may well apply to the whole decision-making process including means as well as goals. More often than not, our goals are ambiguous therefore, even the identification of that which constitutes a proper means becomes highly problematic. The kind of ambiguity we are referring to should not be mistaken with anything related to some kind of linguistic confusion that can be somehow resolved in one way or the other. The ambiguity we are introducing is just a symptom of the complexity often characterizing decision making and problem solving. Consider, for instance the following two problems: scheduling a meeting with five colleagues and figuring out how to increase cooperation among team members. Indeed, scheduling a meeting with colleagues may turn out to be quite hard. Yet the goal is clear and it can be achieved directly by making use of appropriate means. In contrast, figuring out how to increase cooperation is inherently ambiguous due to the complexity of the goal itself. That is to say, it is not possible to take the goal and work back to derive the sequence of the right means — even a subset of those, as the traditional view on BR would assume. We may therefore argue that the type of engagement with the environment (and the world) is fundamentally of a different nature. Such an engagement is rooted in the disposition to renounce to the certainty of a plan specifying means and goals beforehand, and consequently to engage the environment (and the world) in a series of attempts aimed to find a possible way through in due course (Chia and Holt, 2009; Secchi, 2016).
Simon suggested that the engagement with the environment is central to bounded rationality not only as a source of constraints, but also as a source of resources. The notion of ‘docility’ — which Simon focused on in the very last part of his career (1990, 1993) — might be viewed as an attempt to bridge this gap. Docility is defined by Simon as the tendency exhibited by those agents who rely more than others on the information provided through social channels to make decisions. What “social channels” means may vary from case to case, especially after the advent of the web (Secchi, 2011; Magnani et al., 2007). It may mean to rely on other people’s direct advice or on other surrogated forms that are chiefly mediated, for example, by technological devices (i.e., smartphones) or services (i.e., social media like Facebook or twitter, web search, etc.). In general, as we have already argued somewhere else (Bardone, 2011; Secchi and Bardone, 2009, 2013), what is central to the docile individual is that the decision maker acts in such a way as to presuppose the existence of a community or a social group to refer to. Therefore, docile individuals are those who rely on sharing ideas, and feel committed to doing so with like-minded people. In other words, they fundamentally take a more collaborative and cooperation-based stance on decision-making.

Although the notion of docility represented a possible way to go beyond the received view of bounded rationality, it is characterized by a number of shortcomings that have been already discussed in detail in previous studies (Secchi and Bardone, 2009, 2013; Secchi, 2016). Chiefly, the main problem with docility as it was presented by Simon is that it does not fully acknowledge the variety of ways in which an agent may actually engage with the so-called social channels. For example, it is not entirely clear if the reliance on social channels is merely passive. Or if we can identify a more active side, which would — at least in theory — specify a type of docile individual that would be more prone to creating rather than simply sharing information. In presence of such theoretical problems, it is hard to assess whether the notion of docility can really have an impact on the way in which bounded agents may really act, despite the growing interest in recent works (Bardone, 2011; Knudsen, 2003; Miller and Lin, 2010; Ossola, 2013; Secchi, 2011; Thomsen, 2016). Docility has the function of understanding rationality and cooperation when interactions within a group are stable and well defined but it is unclear how much this concept is useful when groups are formed ad hoc or when the decision maker reaches out to members of other groups.

In this work, we aim to take docility seriously, but at the same time work out a more multifaceted view that docility seems to lack. That is, a more active, forward-looking and creative side. In order to bridge this conceptual gap, we propose to term inquisitiveness the specific type of engagement with the environment and its resources. We use the word “inquisitiveness” to refer to an agent who mostly relies on learning by inquiry and open explorations of his or her own environment, including social channels.

The introduction of the notion of inquisitiveness is a distinct departure from the received view on BR, because it identifies the main element of rationality in its bounds, prompting the agents to learn from open-ended inquiries and to commit themselves to the complexity of decision-making. In a way inquisitiveness may be considered a further elaboration of what has been referred to in the team performance literature as “openness to cognitive diversity” (Klein and Kozlowski, 2000) and, more recently, “cross-understanding” (Meslec and Graff, 2015) — both pointing out the importance of “being open”. The novelty that inquisitiveness is meant to introduce in this field regards the reference to inquiry as an open-ended activity, which, in a broader sense, has the main function to allow the individual to cross pre-existing boundaries of cooperation to establish new ones.
1.2 From Docility to Inquisitiveness

As far as this paper is concerned, we develop the notion of “inquisitiveness” in order to try to go beyond the received view of docility that we have briefly sketched above. Our main aim is therefore to introduce a different conceptualization of boundedly-rational agents precisely based on inquisitiveness.

As we noted above, docility identifies a class of individuals — the docile individuals — which are characterized by reliance on the information provided by social channels along with a general inclination or disposition to share ideas with like-minded people and thus collaborate (Simon [1993], Knudsen [2003]). Docility, however, seems not to cover one important aspect characterizing boundedly-rational agents. We argue that this aspect deals with the question of boundaries (Secchi [2016]). We posit that docility refers to those situations in which a person works with other people on something (e.g., a project) that is — or to a large extent is — already defined. This is, for example, a characterization very close to what Thomsen [2016] uses to characterize teams of medical doctors and nurses in the emergency room of a hospital. This characterization does not imply that the type of job one is engaged with is then dull or highly routinized, as the healthcare-related example hints at. It means that the docile individual tends to work within boundaries that are set beforehand and that, therefore, characterizes the extent to which an individual shows cooperative behavior and his or her willingness to cooperate with other people. The boundaries affect also the way in which docile individuals act. In this respect we adopt Simon’s point of view, according to which docile individuals are fundamentally passive in the sense that they do not contribute much to the creation of new cognitive resources. They are also passive in the sense that they tend to work within what we may generally refer to as a paradigm (Kuhn [2009]), which by definition specifies acceptable beliefs, perspectives and norms to comply with within a given community. That is, it is a worldview specifying already accepted templates of thinking along with the identification of specific and well defined problems and issues to deal with. Moreover, the docility that an individual shows — i.e., his/her willingness to cooperate with other people — also implies that the docile individuals exercise their sociability towards members of the community or group they belong to rather than expanding the disposition to exploit social channels independent of the community or group of reference (e.g., Magnani et al. [2007]). As docility spreads and reaches high levels among individuals, it also supports the formation of tight couplings among team members and, possibly, an entire organization. If that is the case, then there is a risk that the organization becomes unfit to learn and adapt to the external environment (e.g., Rivkin [2000]), reaching what Siggelkow and Rivkin [2005] call “sticking points” (p. 108). These are aspects from where the agent would not move away from.

Conversely, inquisitive individuals are rather different. Inquisitiveness is not to be thought just as a “wild” enhancement of docility because it works on docility in a very specific way. From a cognitive point of view, it is what breaks received patterns of behavior and allows individuals to see unexpected and serendipitous connections among apparently unrelated things (Bardone [2011]). From a social point of view, inquisitive individuals reach out to others to explore problems more broadly and facilitate a solution (Secchi [2011]), hence the establishment of loose coupling mechanisms in the organization becomes one of the implications of this behavior (as it is apparent from some of the literature on search; e.g., Knudsen and Levinthal [2007], Rivkin [2000]). The way these individuals interact with others is oriented toward gaining a better understanding of the problem at hand. Their use of information is not simply the sum of what is available from others but a thoughtful reorganization of knowledge with the aim of finding a suitable application. In this sense they are essentially driven by a “thirst” for
knowledge and understanding, which is found in the way in which they interact in their immediate social environment. Because of all this, they potentially bring collaboration to a different level. If docility allows collaboration to emerge within a pre-defined frame or group of people, inquisitiveness has the potential to establish new ones, both within and outside the group one works in. This is in contrast with the literature on ‘shared cognition’ (e.g., Cannon-Bowers et al., 1993; Cannon-Bowers and Salas, 2001), where individuals share a mental model to make the team more effective. Instead, we do not assume that holding similar views necessarily pays off. Nor do we say that the opposite does it. What we argue is that inquisitiveness, that is, being open to learning and engaging other people regardless of their background, position, and role within an organization, may lead to better problem-solving capacities. In a way we may say that we do not focus so much on sharing as being open. Besides, unlike the proponents of shared cognition, we do not hold the view that cognition is information processing that happens within the skull of otherwise socially connected human beings. We hold the view that cognitive activities are essentially distributed (e.g., Cowley and Vallee-Tourangeau, 2013; Hutchins, 1995; Magnani, 2007), which means that both the doing/practicing and the more systemic dynamics of interaction have priority over the computational measurement of what is shared (Bardone, 2011; Secchi, 2011; Secchi and Adamsen, 2017). From this perspective, inquisitiveness can be thought of as docility operating free of the group bounds; under this basis, it can be said that it ‘upgrades’ docility, to some extent.

The following section describes how we built these elements in a computational simulation model.

2 The Model

We used agent-based simulation to explore the impact of inquisitiveness in problem solving. Inquisitiveness is seen as a tool that links agents together, hence it affects how teams and groups deal with problems. Agent-based modeling (ABM) is a simulation technique that has been increasingly used in the social sciences (e.g., Secchi and Neumann, 2016; Fioretti, 2013) and its properties have recently been explored in relation to teams and groups (Secchi, 2015). In line with this literature, this paper applies the concept of inquisitiveness to groups concerned with problems.

In the following, the model is described in its basic functions with reference to the ODD (Overview, Design concepts, Details) protocol (Polhill, 2010) and with the broader Design of Experiments (DOE; Lorscheid et al., 2012). In this paper we provide a short description of the model, given that the full version and a description of all model functionalities are available online.

2.1 Objectives of the model

The purpose of this model is to understand the impact of inquisitiveness on boundedly rational agents that are confronted with problems. As mentioned above, inquisitive individuals reach out to others to explore problems more broadly and facilitate a solution. The way these individuals interact with others is oriented toward gaining a better understanding of the problem at hand. Their use of information (competence, \( c \) in the model) is not simply the sum of what is available from others but a thoughtful reorganization of knowledge with the aim of finding suitable applications. Given these assumptions, the model attempts to explore whether individuals with highly inquisitive minds deal with problems better than individuals with lower inquiring attitudes — resulting in a better use of their and team members competence.
The model mimics an organizational environment where simulated employees have the task to deal with problems, and teams are build around these problems, if one simulated employee cannot solve the problem on its own. This is done to represent the opportunity to work with unstable and ad hoc groups, to study the features that characterize inquisitiveness (as described above).

2.2 Agents and parameters

The model has two separate types of agents: problems \( (P) \) and decision makers \( (dm) \). The former elements are defined by their level of difficulty \( (d) \) so that every problem is associated with a random-normal value for this parameter. The latter agents — the decision makers — each have a level of competence \( c \) that is initially distributed normally at random across the population. The competence level \( c \) is an agent’s knowledge and it can be applied to a problem as a direct function of the efforts necessary to find a solution. In other words, \( c \) can be thought of as a set of cognitive abilities that each and every individual has, in line with the tradition of studies on BR (e.g., [Kahneman 2003][Gigerenzer and Selten 2001]). These are operational abilities because they can be applied to problem solving. In fact, if \( c > d \) then a problem gets solved, and competence of the agents responsible for finding a good solution increases at a fixed rate \( \gamma_i \) in \([0.15, 0.30]\). When a solution cannot be found, then the competence rate slightly decreases of \( \gamma_d \) in \([0, 0.05, 0.1]\). This information is updated at every step of the simulation. All parameters and respective values are summarized in Table 1. A difficulty level \( d \) for each problem is not interpreted as an objective value because it depends from competence levels \( c \), the combination of agents around a given problem, and the disposition of the agents to share and combine \( c \).

Other characteristics of decision makers \( dm \) are enquiry \( e \), and socially-oriented decision making sodm or, as we called it above, ‘docility’. Those \( dm \) with sodm \( i \) < \( \mu_{sodm} - 0.75 \cdot \sigma_{sodm} \) are less prone to use information from social channels to make decisions. Instead, those with sodm \( i \) > \( \mu_{sodm} + 0.75 \cdot \sigma_{sodm} \) are particularly keen on using information from social channels (other agents in the system) to make decisions. This is in line with previous models of docility (Simon 1993; Secchi and Bardone 2009; Secchi and Gullekson 2016), where individuals in a system have difference dispositions towards giving and taking information, recommendations, advice from others. And this is the function of the numerical value of sodm. The other characteristic mentioned above, \( e \), is attached to each agent using a random normal distribution. When the level \( e_i \) of a particular agent \( i \) is higher than the mean \( \bar{e} \) then there are higher gains from cooperating with others. This feature of the model is incorporated to describe inquisitiveness as integrated with (although different from) docility. While high sodm signals the ability to be taught (hence to learn from others), \( e \) is that sense of openness (see above) that makes one to take the problem seriously and explore or look for solutions outside of the boundaries of the social community (team) one is accustomed to. It is clear that combinations of the parameters above depict salient aspects of how individuals interact in organizations. In particular, sodm \cdot c is the amount of competence that one is willing or able to share with others.

Each \( dm \) scans the environment around it with a certain range (Table 1), and connects with problems and other agents around it. When other agents and/or problems are in range then connections are established. The agents then start sharing their knowledge \( (c) \) and they adopt different rules for doing that depending on their sodm levels and their \( e \) levels. First of all, knowledge/information is shared on the basis of sodm so that higher values lead to a better access to one’s competence \( c \). Also, agents with higher levels of sodm embed other’s knowledge according to a non-linear effect, that is \( \sum_j c_i + (sodm_j \cdot c_j)^{sodm\cdot c} \), where the parameters
Table 1: Parameter Notations and Values

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Values</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>steps</td>
<td>500</td>
<td>The number of opportunities that agents have to interact with each other when dealing with problems.</td>
</tr>
<tr>
<td>initial number of problems, ( N_{P,0} )</td>
<td>100( i ), 200( i ), 300</td>
<td>Initial number of problems in a given environment (organization), i.e. at time zero</td>
</tr>
<tr>
<td>problem spin-off, ( pso )</td>
<td>2( i ), 4( i )</td>
<td>This is the top number through which problems can multiply at any step of the simulation.</td>
</tr>
<tr>
<td>initial number of decision makers, ( N_{dm,0} )</td>
<td>100( i ), 200( i ), 300</td>
<td>Initial number of decision makers in a given environment (organization), i.e. at time zero</td>
</tr>
<tr>
<td>difficulty, ( d )</td>
<td>( \sim \mathcal{N}(3, 1)^{\dagger} )</td>
<td>Each problem is associated with a difficulty level, random-normally distributed.</td>
</tr>
<tr>
<td>competence, ( c )</td>
<td>( \sim \mathcal{N}(1, 1.5)^{\dagger} ), ( \sim \mathcal{N}(3, 1.5)^{\ddagger} )</td>
<td>This is the knowledge — associated to each decision maker — that is needed to solve a given problem.</td>
</tr>
<tr>
<td>competence increase rate, ( \gamma_i )</td>
<td>0.15( \dagger ), 0.30( \ddagger )</td>
<td>The rate at which competence increases if a problem is resolved.</td>
</tr>
<tr>
<td>competence decrease rate, ( \gamma_d )</td>
<td>0( \dagger ), 0.05( \ddagger )</td>
<td>The rate at which competence decreases if a problem is not resolved.</td>
</tr>
<tr>
<td>socially-oriented decision making, ( sodm )</td>
<td>( \sim \mathcal{N}(0, 1) )</td>
<td>This is the docility of each agent and measures, on average, how much one leans on information coming from others to make decisions.</td>
</tr>
<tr>
<td>enquiry, ( e )</td>
<td>( \sim \mathcal{N}(0, 1)^{\dagger} )</td>
<td>This is the enquiry level that would facilitate agents dealing with knowledge (competence) coming from others in the simulated organizational environment.</td>
</tr>
<tr>
<td>inquisitiveness</td>
<td>true( \dagger ) / false( \ddagger )</td>
<td>This triggers the different ways that agents have to deal with groupwork.</td>
</tr>
<tr>
<td>range</td>
<td>6( \dagger )</td>
<td>This is the value used to explore the environment that surrounds each agent.</td>
</tr>
</tbody>
</table>

*Note.* \( \dagger \) = parameter values included in the first simulation test; **bold font** = parameter values included in the simulation discussed in the analysis.

Indexed with \( i \) refer to the agent and those indexed with \( j \) refer to other agents in range and connected to the agent \( i \). Those with lower levels of \( sodm \) use a **linear** effect, \( \sum_j c_i + sodm_j \cdot c_j \). The **non-linear** effect is only possible when agents reach out of their standard approach to the group when dealing with a problem. The assumption of this model is that inquisitiveness triggers individuals to process information coming from social channels in a way that combines
their competence with the competence of others producing effects that may be valuable to problem solving. In the simulation, it is possible to switch inquisitiveness ‘on’ and ‘off’ (Table 1) to understand when such an attitude towards group decision making produces better outcomes (i.e., solves problems more efficiently). The non-linear effect operates in the model for high e and sodm agents only when inquisitiveness is turned ‘on’. This should also represent serendipity and open-endedness of cooperation activities, i.e. something that goes beyond established boundaries.

The model is also dynamic in that both dm and P may change as they interact. Most successful decision makers serve as example for others, so that they attract other agents that will try to behave like them in the following step (or interaction time) of the simulation. To represent uncertainty of external conditions, a random number of up to 3 problems with $d \geq \max d \times 0.95$ increase their difficulty at a 2% rate and one of them creates up to 4 other ‘small’ problems, i.e., of low difficulty. This latter procedure is called problems spin-off in the simulation and it is summarized in Table 1.

Finally, both problems P and agents dm appear randomly in the simulated environment. While the problems do not move at all in the simulation space, the agents move around and try to find problems to solve. The dm’s task is to find problems to solve and create a team or group of other agents around that problem if it cannot solve it solely with its own competence level c. If, as dm move to reach a certain problem, they find another P, they stop and attach themselves to it in an attempt to solve it. When connections to problems are established agents do not move until those problems are solved.

2.3 Process overview

There are four steps in the simulation process. First, the agents are distributed on the two-dimensional simulation space at random and are attributed the characteristics described above. Second, the agents behave according to rules of interaction so that dm agents go find problems, connect to them and to each other. These rules regulate team formation and problem finding based on range (see above). For agent-free problems — i.e., problems that may not be in range —, the rule is that dm select one random problem and move towards it. If, while the dm agent is getting to its agent-free problem, they happen to pass by a problem that is in range, then the dm agent connects to this one and forgets about the problem it was aiming at previously. Third, agents try and solve the problem with their own knowledge $c_i$ and, if that is not enough, they combine knowledge from others $c_j$ according to inquisitiveness levels (or its absence). We refer to those rules as linear and non-linear effects (see above); the latter being those for more inquisitive agents. Fourth, dynamic interaction is added to the model so that the problems hatch and/or increase in difficulty. Also, dm agents increase or decrease their competence and eventually change their general attitudes towards problem solving (sodm), depending on results of the previous round of interactions.

3 Procedures and results

This section introduces the simulation procedures, the logic behind the choices for the runs, and the findings resulting from testing the model. The simulation turned out to be complex due to the large number of parameters included. Hence, in order for the analysis and results to effectively indicate a direction in which this research can be moved forward, we ran the full model and present only a selection of the most promising results in the following pages. The full model and additional information are available online.
3.1 Implementation and procedures

The model was implemented in NetLogo 5.2, a free software for agent-based modeling (Wilen-sky, 1999). We performed several runs with a full factorial design with the parameters summarized in Table 1: \(2 \times 2 \times 2 \times 3 \times 3 \times 2\) for a total of 288 configurations (the \(\dagger\) sign indicates values included in this first test). As indicated in a recent studies (Secchi and Seri, 2016; Seri and Secchi, 2017), power analysis is an efficient tool to estimate the number of runs a simulation should run (for applications, see Secchi and Gullekson, 2016; Radax and Rengs, 2010). An attempt to reach a power of 0.95 at the 0.01 significance level, and a conservative estimate of effect size, 0.1, resulted in approximately 30 runs per each simulation. The 288 configurations ran 30 times for a total of 500 interaction times (steps).

3.2 Findings

Results of the simulation are presented in two separate but complementary ways. On the one hand, Table 2 shows results of three fixed-effects regression models that intend to give the full picture of what affects problem solving. On the other hand, results are also presented on Figure 1 and Figure 2 to provide a visual representation and detail our understanding of the effects.

Table 2 presents three regression models calculated using the R package ‘plm’ (Croissant and Millo, 2008). All the models use the number of problems solved at time \(t\), \(N_{P,t}\), as the dependent variable and differ one from the other for the initial number of problems \(N_{P,0}\) the simulation starts with — i.e., Model 1 estimates coefficients when the starting point is 100 problems, Model 2 does that with 200, and Model 3 with 300. Variability in the three models is particularly wide, since the data is only limited by the initial number of problems in the system (or organization) so that these results can be considered very general and are probably a good starting point for the analysis.

All three models fit the data well (\(F – stat\) at the bottom of Table 2) and explain a significant proportion of the variation in the dependent variable (\(R^2\) is respectively 0.74, 0.72, and 0.51).

The number of problems solved is generally positively affected by the condition of inquisitiveness, making agents enhance their capacity to interact with others and allows the more ‘docile’ (HD in Table 2) to combine group resources (i.e., competences) with a multiplicative factor. In the simulation, inquisitiveness is a boolean variable and it can be ‘true’ (on) or ‘false’ (off). The anchor for the results in the model is the ‘false’ condition, meaning that the coefficients express what happens to the dependent variable when the parameter is ‘true’. The strongest effect, \(\beta = 2.876, p < 0.001\), is present when the initial number of problems \(N_{P,0}\) is set at the highest level (300), and also similar in Model 1, \(\beta = 2.483, p < 0.001\), for the lowest number of problems. It is apparent that inquisitiveness has a marginal although stable direct effect on the number of problems solved in spite of the number of problems in the system.

Other coefficients in Table 2 are the estimates of the competence levels of high-sodm (HD) and low-sodm (LD). The latter uses a linear approach to group shared competences to approach problems while the former use a non-linear approach. When the parameter inquisitiveness is in place (i.e., set to ‘on’) then those HD agents with enquiry above the mean have better ways to combine group members’ competence into the task to be performed or problem to be solved. With this in mind, the performance on a given problem depends on the agent that finds a connection to that particular problem and the group of other agents included in the task. Since HD agents are more susceptible to adaptation, low competence of the group may drain the overall competence level down more quickly than the competence of LD agents that are less adaptable and use a summative (or linear) approach to problems. The interpretation of results is that HD with highly inquisitive skills work better when the group members have something to
Table 2: Fixed effects regression models of parameters affecting the number of problems solved

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Number of problems solved</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1 Prblms=100</td>
</tr>
<tr>
<td>HD Competence ($c_{HD}$)</td>
<td>12.443*** (0.538)</td>
</tr>
<tr>
<td>LD Competence ($c_{LD}$)</td>
<td>10.974*** (0.498)</td>
</tr>
<tr>
<td>Number of DM ($N_{dm,t}$)</td>
<td>0.216*** (0.002)</td>
</tr>
<tr>
<td>Problem spin-off (high) ($pso$)</td>
<td>100.799*** (0.358)</td>
</tr>
<tr>
<td>Problem difficulty (average) ($d$)</td>
<td>41.187*** (0.775)</td>
</tr>
<tr>
<td>Inquisitiveness</td>
<td>2.483*** (0.360)</td>
</tr>
</tbody>
</table>

Observations 32,026 28,018 26,855
R² 0.744 0.724 0.510
F Statistic 15,462.770*** df = 6; 31919 | 12,224.820*** df = 6; 27911 | 4,642.395*** df = 6; 26748

Note: *p<0.1; **p<0.05; ***p<0.01. DM = decision makers; Prblms = problems; the base model is Model 1: DM=100, Prblms=100.

offer and it is less effective when the ‘quality’ (i.e., skills or competence) of the group is scarce. In general, in a system with fewer problems the competence of the HD agent seems to have a more effective impact in dealing with the task of problem solving ($\beta_{mod1} = 12.443, p < 0.001$) and it decreases steadily with the increasing number of problems ($\beta_{mod2} = 9.825, p < 0.001$; $\beta_{mod3} = 7.015, p < 0.001$). Something different happens for the competence of LD agents. Their competence is more effective than HD agents in Model 2 ($\beta = 12.407, p < 0.001$) and Model 3 ($\beta = 8.835, p < 0.001$).

To better understand the role of the different types of agents and of inquisitiveness, we also represented some of the relations among parameters in Figure 1. This and the following figure show competence levels measured in the left y axis, per HD and LD agents as they evolve over time ($x$ axis is re-calibrated on a 0-100 scale). The same left $y$ axis is used to measure problem average difficulty. The right $y$ axis is based on a different scale measurement and reports the number of problems in the system at any given time step ($x$ axis). In Figure 1 there are two lines for each parameter, one for when inquisitiveness is ‘off’, one for when it is ‘on’.

The lines in Figure 1 are regression curves for the given set of conditions in the simulation. When initial conditions are $dm = 100$, and $P = 300$, and inquisitiveness set to ‘on’, after a first increase, there is a very slow decrease of competence for HD agents while LD competence levels remain approximately stable around 1.5. The number of problems steadily declines even
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Figure 1: Competence, problem number and difficulty for \( pso[2, 4] \), \( N_{dm,0} = 100 \), and \( N_{P,0} = 300 \)

when difficulty \( d \) increases slightly. The first 40 rounds (steps) seem to be for \( dm \) to find a level of competence that is appropriate for the problems to be dealt with. Under these conditions, inquisitiveness produces the effect of making problems more easily solvable with an average lower level of competence \( c \) needed for the HD, i.e. those who non-linearly combine efforts of the group members. This probably means that the way to combine competences together in a group is more efficient when the inquisitive HD agent operates. This is based on the fact that the curve for the number of problems when inquisitiveness is ‘on’ declines more rapidly.

Interestingly, the initial number of \( dm \) \( N_{dm,0} \) has a very low impact on problem solving, with the coefficients ranging from 0.216 and 0.301 (Table 2). These are very low values compared to the others in the regressions and, in particular, if compared to the impact of how many problems are generated at every round (i.e., step). Figure 2 exemplifies this aspect and shows a detail that sheds some light on the effects of \( N_{dm,0} \) in the simulation. First of all, a note on how to read the curves is deemed necessary. As mentioned above, these are estimated regression curves based on the simulated data. For example, in Figure 2, around time 30 when \( dm = 300 \) all 100 problems are solved and the regression data estimates the trend as if the original conditions replicate themselves, i.e. it forecasts the values for the remaining steps.

There are two interesting points to highlight from Figure 2. One is that all \( P \) are solved rapidly when the average competence levels are above the average difficulty levels. When this does not happen, the interaction between decision makers and problems takes more time and more effective group work. The other is that the artificial (probably surreal) situation where there are more \( dm \) than \( P \) increases competence \( c \) of both types LD and HD, irrespective of the way competences of the group are combined (i.e., linearly or non-linearly).

The problem spin-off (\( pso \)) is coded as a dummy in the regression because it only has two
options and they only indicate the maximum number of problems that may be generated at any given step of the simulation. Hence, we have a lower bound, 2, and a higher bound, 4. The coefficients are calculated using the lower bound as an anchor; when \( pso \) is high, the impact is extremely strong on the problems solved. This is probably due to the fact that the difficulty of these new problems is relatively low, hence the likelihood that they are solved quickly is very high. When there are more problems to deal with in the system, the impact of new problems slows down (\( \beta_{mod2} = 88.983, p < 0.001, \beta = 81.244, p < 0.001 \)). By comparing the effect of the presence and absence of some conditions, we can understand results from Table 2 better. For example, when \( N_{P,0} = 300 \) and \( N_{dm,0} = 100 \) and inquisitiveness is off, the impact of \( pso \) causes more problems to be solved, on average, and significantly decreases the competence level for HD agents, to the point where they are less competent than LD agents. When there is the possibility that problems multiply at a higher rate, the absence of inquisitiveness determines the linear combination as the best fit for the system and problems are solved at about the same rate as when \( pso = 2.5 \).

Finally, the average difficulty of problems also has a strong positive impact on the number of problems solved. This may seem counterintuitive at first. Higher difficulty should be symptomatic of less problems solved. However, in the simulation some problems may reach a very high difficulty — remember that problems that are not solved and have \( d \approx \max d \) tend to become more difficult — while the vast majority keeps a level that makes them more likely to be dealt with. Also, extremely difficult problems are more likely to generate some other small satellite problems that are, on average, solved in one or two of the following steps of the simulation. Hence, the higher the mean difficulty the more likely is that there are problems that can be solved relatively easily. Harder problems stay there for longer than the average.
problem because it takes longer to find a solution. Hence, they also attract more agents around them and the working team tends to expand. This also means that the spin-off problems are dealt with and solved quite easily, due to a network effect. Another effect here is that agents have a boost in their competence due to solving smaller problems. This, in turn, helps them dealing with the more complicated problem. In short, more difficult problems push agents to work together (the network effect) and harder (their competence levels raise). The impact increases with the initial number of problems $N_{P0}$ in the system ($\beta_{mod1} = 41.187, p < 0.001$, $\beta_{mod3} = 84.661, p < 0.001$). Some of these effects can be seen from Figure 1 above.

4 Implications and conclusions

Drawing on the late Simon (Simon, 1990, 1993), this paper introduces a refined version of BR that is socially-oriented. In particular, it makes the distinction between those individuals who operate within the boundaries of their team or group following its norms (i.e., docile), and those who extend their reach outside of those boundaries and norms (i.e., inquisitive).

This study posits that inquisitiveness builds on docility and it works as a resource availability enhancement. In the model, inquisitiveness is designed so that agents would combine team member competences in a way that makes problem solving more efficient. This is because the integration of knowledge from the various team members is done non-linearly, i.e., exponentially increasing or decreasing the original knowledge base of the inquisitive individual (HD in the model). Instead, other non-inquisitive individuals would combine competences in a linear fashion and this makes knowledge integration more directly dependent on the existing competences. In other words, the inquisitive team member seems to add something to competences that is not included in the original knowledge base of each team member. This synergy has potentials to increase the efficiency of knowledge integration when dealing with problems. One implication following the results of the simulation is that less competence seems to be necessary, at the system level, to solve a higher number of problems. Inquisitiveness brings in more problem solving efficiency in the system.

In more practical terms, this means that what counts in an organization is not necessarily the single piece of expertise that each individual may bring in. Conversely, what seems to count is more related to the attitude that each individual has in relation to the problems the organization is facing. So, for example, in a group of researchers interdisciplinarity might not be the solution, as it still relies on the idea of static expertise. Conversely, it is the open-mindedness and curiosity of the researchers — which may come from the very same disciplinary background — that may help cross gaps among disciplines and subsequently bring about new and innovative perspectives, which would be simply unthinkable in the rigid confines of well-defined expertise. How this may actually happen is a matter that only an empirical investigation could deepen.

The impact of inquisitiveness appears to be particularly effective when the number of problems in the system is particularly high. This implies that inquisitive features are serving the team better when there are multiple fronts to deal with. This may be relevant to those organizations that face a crisis or operate in turbulent environments. Employees that are capable of crossing the norms of their group and of integrating knowledge on a wider basis can make a better use of human resources. Here again, more concretely, this may suggest that inquisitive people better adapt to uncertainty and they are consequently a better fit in turbulent environments because that is not after all so far from their usual way of going about things. That is, in a way they are already working with uncertainty and they are inclined to use it to their advantage. Crossing the norms and boundaries of pre-defined groups, inquiring and exploring
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further possibilities, being driven by curiosity — these are all elements that feed and, in turn, are fed by uncertainty.

Also, when organizations have several problems, inquisitive individuals seem, on average, to find ways to increase their competence more rapidly than other agents in the system. This is partly due to the assumptions we used to generate the model. However, what comes as a surprise in the simulation is that this does not happen constantly through time. Instead, once competence $c$ reaches a certain level, it almost always stabilizes on that level. Whether this level can be called “equilibrium” is a question for another study. That being said, it is certainly interesting to notice that the $c$ level is such that the number of problems left continues to decrease. This may mean that a particularly curious person (who, therefore, would exhibit a higher level of inquisitiveness) may quickly become familiar with a certain domain or task, as he/she is mostly driven by his/her thirst for learning and understanding. Once he/she attains a certain level of competence or familiarity, he/she may just turn his/her attention to another problem and start from scratch.

There are some limitations in the approach that we have taken to study the proposed model of rational decision making. First, competence $c$ is represented by a number and that is an extremely simplified version of the way knowledge actually materializes. This calls for expanded and more sophisticated modeling. Second, the model only considers ad hoc teams for a number of problems. In this respect, these are like task forces that deal with something that is in the system although they are consistent with the activities of inquisitive people. Future evolution of this model may well consider teams operating on a more stable set of relations to explore how inquisitive people affect them. Third, additional organizational features such as power, hierarchy, rewards, and similar can and probably should be added in an improved version of the model. Finally, the $pso$ procedure may eventually produce spurious results because it affects the very essence of the effects we are measuring. An interesting step forward would be to compare a model with and another without $pso$.

The paper shows how the two characteristics play around with individuals and their problem solving abilities. It shows that BR can and should be considered as a social process and team dynamics unveil how social attitudes help problem solving. As far as our knowledge is concerned, this study specifies for the first time and in a more practical way how rationality is extendable (Secchi, 2011) and what are the individual characteristics that enable chance seeking as a way of inquiring (Bardone, 2011).

Notes

1 In this paper, we do not attempt to make a difference between groups and teams, hence the two terms are used interchangeably.

2 Materials is available on OpenABM at [https://www.openabm.org/model/4749/version/1/view](https://www.openabm.org/model/4749/version/1/view). Materials include: full code, NetLogo 5.2 version, implementation notes, and parameter manipulations. Model versions are updated as we keep working on the code.

3 The selection of parameter values was done in relation to their combined effects — for example, the distribution of $c$ cannot be too far from $d$ or no problem is solved — and most values were calibrated during several pilot tests.

4 The fixed-effects model was chosen as a result of Hausman tests performed on each of the three configurations of the models. The test compares a fixed-effects model to a random-effects model (Greene, 2008) and tests whether the error terms of the specified effect (time, in this case) are correlated with the constant (i.e., the intercept) or not. On average, the test shows that the fixed effects provides better estimates: Model 1, $\chi^2 = 18.48, df = 6, p = 0.005137$; Model 2, $\chi^2 = 11, df = 6, p = 0.08837$; Model 3, $\chi^2 = 83.836, df = 6, p = 0.00000$.

5 The figures derived from the split of parameters can be found on the OpenABM platform where the model is located: [https://www.openabm.org/model/4749/version/1/view](https://www.openabm.org/model/4749/version/1/view)
References


