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# Cognitive attunement in the face of organizational plasticity

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The IOP Model (updated to 2.1.1) is available here:

<https://www.comses.net/codebases/4ff566a6-c0f8-4ca2-aa5f-21d44705aea8/releases/2.1.2/>

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## Abstract

**Purpose** — The paper uses part of the distributed cognition literature to study how employees cope with *organizational plasticity*, in an attempt to identify the characteristics of *cognitive plasticity*.

**Design/methodology/approach** — Evidence is collected by designing and implementing an agent-based computational simulation model (the IOP 2.0) where employees have the option to use external resources and the social environment to perform tasks. Since plasticity is more effective when change and uncertainty are high, the simulation features an increase in the difficulty and number of tasks to which employees need to cope.

**Findings** — Cooperation and sharing of competence and ability are key to cognitive plasticity. Being able to master the use of some resources, together with other employees competencies make some achieve the most efficient task performance.

**Practical implications** — Findings suggest that, under conditions of change and plasticity, HRM shall attempt to develop measures to support employees' cognitive skills necessary to cope with it, for example, mostly through diagnosis, training, and facilitating on-the-job dialogue.

**Originality/value** — This is the first study that attempts a merger between organizational cognition and plasticity, and it is the first to match its results to HRM policy recommendations.

**Keywords:** agent-based modeling, organizational cognition, task complexity, competencies, abilities

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## Cognitive attunement in the face of organizational plasticity

### Introduction

It is common to read and hear statements about how uncertain and dynamic the business environment has increasingly become (e.g., Reeves et al., 2016). Perceptions of complexity require action, if organizations wish to survive or, to take a more proactive stance, to prosper. Over the years, this has brought business scholars and practitioners to search for structures and forms that would help organizations cope with an ever changing environment. Some discuss — as do other articles in this Special Issue — about *plasticity* (see also Herath, 2019; Levinthal and Marino, 2015), while others stress the need to revamp efficiency and suggest an *agile* approach to management (e.g., Worley and Lawler, 2010; Worley et al., 2014). Yet others indicate the benefits of flexible organizational arrangements due to, for example, a relaxation of formal structure (Lomi and Harrison, 2012; Herath et al., 2016, 2017).

This article studies organizational flexibility and adaptability (called *plasticity* here) by positioning cognition at center stage. Why would this be necessary and why is it important? It is necessary because, on the one hand, by studying cognitive processes one enquires on the effects that organizational fast-paced adaptation and change bring to individuals (Bardone, 2011) and on the relations they establish with others, external resources, and the organization at large (Hodgkinson and Healey, 2008). In other words, cognition seems necessary to understand *top-down* influences of change on employees. On the other hand, the study of cognition becomes even more central when change is driven by individuals and their interactions, i.e. to what can be called *bottom-up* change. The two influences are clearly intertwined, but an example of the former (i.e. top-down) would be the case of a sudden change in organizational structure, carrying implications on the access to the resources required to perform a task (e.g., DiFonzo and Bordia, 1998). Another such examples would be that of the intended and unintended implications of broader organizational change such as the introduction of wellness programs on employee behaviors (Secchi et al., 2015). An example of the latter (i.e. bottom-up) would be that of a new hire that brings in specific competencies with potentials to improve standard operating procedures. In this example, change is not as sudden as in the previous case, but may happen, if management makes room for it (e.g., Grove, 1999). The point is that these cases require an understanding of how cognitive processes evolve, change and, most importantly, adapt to an organization's dynamic evolutions, more so when they are abrupt and disruptive. If we do not establish a link between the micro (cognitive) and the macro (organizational) aspects of change, the basic mechanisms of *plasticity* may be very difficult to understand and/or implement. This aspect brings us to reflect on the importance of this line of research.

Most cognition research in organizations has been carried over with a rather individualist focus (Secchi and Adamsen, 2017), hence with a strict organizational behavior angle (e.g., Hodgkinson and Healey, 2008). This approach gives a good grasp of the mechanisms leading to, for example, task performance (e.g., Jundt et al., 2015), it is usually not concerned with macro organizational elements, nor it is about organizational dynamics that change over time. However, if any organization is an adaptive dynamic system (e.g., Giannoccaro et al., 2018),



then some of this adaptation can be tracked down to the actions of their participants. This leads to the fact that understanding organizational cognition is extremely important if not crucial to uncover the ties that individuals maintain with the broader macro organizational dynamics (this point has been made in Secchi and Cowley, 2018). And it is exactly this understanding that is a typical concern of Human Resource Management (HRM), as the micro-macro tie can be used as a leverage to gain insights on hiring, employee development, strategic positioning of personnel, and on improving interactions between layers and competencies (e.g., Leme Fleury and Correa Fleury, 2005; Diaz-Fernandez et al., 2015).

The paper focuses on understanding how cognitive plasticity attunes with organizational plasticity. The latter can also be defined as characterized by uncertain flexible organizational dynamics and the attunement can be framed as a way to find a coping strategy. Results indicate that two such strategies emerge. One, called *concentration*, is a strategy that emerges when employees stick to the tasks they consider until they are performed. The other is a *differentiation* strategy and, when adopted, it means that more difficult tasks are discarded such that more tasks are performed. The study shows that behavior associated to distributed cognition should not be applied indiscriminately to organizational plasticity. That is where the role of HRM becomes central. A short review of key concepts that help frame the interaction between these two aspects is offered next. The section following the next presents details of an agent-based computational simulation model (ABM) used to gather evidence to explore the attunement of organizational and cognitive plasticity. The paper ends with the presentation of results on which conclusions are drawn.

## Theoretical background

According to the existing literature, *organizational plasticity* is especially effective when adopted in the face of change (Herath, 2019; Levinthal and Marino, 2015). For this reason, the exploration of the effects on *cognitive plasticity* are analyzed via a perspective — *distributed cognition* — that defines cognition as intertwined with environmental change (e.g., Hutchins, 1995). This perspective is usually specified in relation to a task (Hollan et al., 2000; Cowley and Vallée-Tourangeau, 2017), hence we attempt to define change as it relates to organizational tasks, in order to understand how cognitive processes are affected. The two subsections below succinctly define aspects of the cognitive framework first, and then move to the implications of change and adaptation for organizational tasks. While the latter represents the macro framework, the former is traditionally connected to a micro perspective. Our interest here is to present the two as they are intertwined.

### *The organizational side of distributed cognition*

Most, if not all, of cognition in organizations relates to what Hollan et al. (2000) call distributions to and from “the social group” (p.176). In their view, this means that cognitive resources are distributed among other individuals in the team, department, or organization, intended as the community of reference. While *distributed cognition* (Hutchins, 1995) does not deny nor question the assumptions of bounded rationality (Simon, 1955, 1979), it enhances them in that — especially when one considers the “social group” — it opens the perspective to a wider set of cognitive resources spread in and around each individual (Secchi and Bardone, 2009). From this angle, it is more the work of the late Simon (1993, 1990) that becomes useful. In fact, there he posits that human beings attempt to overcome their rational bounds by engaging in data exchange (e.g., information, suggestions, advice) with other group members, in order to

make decisions. This was originally called *docility* (Simon, 1993) and it has, more recently, been used to identify the behavioral (Secchi, 2011; Bardone, 2011) and organizational (Secchi and Bardone, 2009; Secchi and Cowley, 2018) side of distributed cognition.

However, this identification may be too generic. It is fair to state that distributed cognition as an area of research has grown significantly from its original formulations (especially Hutchins, 1995), to the point where it has merged different traditions and, at the same time, it has evolved into separate and complementary streams. So, the question becomes understanding which one of these streams is more relevant to analyze *cognitive plasticity* and change. The so-called *e-cognition* approach or, as recently re-labeled, *systemic e-cognition* (SEC; Secchi and Cowley, 2018; Cowley et al., 2019) identifies cognition as: *embedded, enacted, ecological, extended, and embodied* (for more details on these streams, see Menary, 2010b; Secchi and Cowley, 2018). The *enacted* and the *extended* perspectives are the two that have instrumental value for the purpose of this study. Although the association is largely fictional, because all the *Es* work together at once, the first can be related to docility more directly, the second has to do with cognitive resources in general.

**Enacted cognition and docility.** *Docility* is described as something that has to do with using information and various other forms of data from other individuals such that they support one's decision making. It is, in other words, an operational concept, it involves action. This may happen in multiple ways, for example, by having a dialogue with another person, by texting, or by writing an email. All of these circumstances include two-way processes where data flows between two or more individuals. Even though there are (can be) relevant repercussions on how these flows affect each individual separately, what matters the most is the creation of a common ground where meaning can be shared (Secchi and Bardone, 2009). *Docility* supports the creation of this shared meaning between individuals, by influencing both perceptions and interconnections. Another way to read these processes is that of considering cognition *through doing* (Magnani, 2007), where it is the data interchange that becomes a cognitive mediator. It is through the actual action toward the others that the meaning, knowledge and/or understanding is made possible. Since cognition is an eminently social phenomenon in organizations, task performance has to do with groups of individuals that "cognize" together. These tensions are captured by *enacted* cognition.

**Cognitive resources at large: the extended stream.** The other area that becomes more relevant when change and task performance are considered, is the stream identified as *extended* cognition (Menary, 2010a). According to the seminal article by Clark and Chalmers (1998), by "distributing" human beings externalize their cognition to the resources they are using. This includes, in the tradition of distributed cognition, mostly artifacts (e.g., Clark, 2003), but it can be extended to include also living beings (Secchi, 2011). There are two main implications of this stance. One is that cognitive resources are not limited to those that can be found in one's brain; the other is that "extension" may be interpreted to be an actual repositioning of one's own cognitive limits (hence moving Simonian bounds of rationality Secchi, 2011). The tasks one considers in his/her work life are performed by exploiting the means that are used to do work, and this action has transformative repercussions on cognition.

#### *The impact of change on organizational tasks*

Micro accounts of plasticity are very limited (Herath, 2019, and other articles in this Special Issue;), since the emphasis has been mostly on macro organizational processes, either strategic (even though they refer to 'flexibility', see Rudd et al., 2008) or macro-behavioral (e.g., rou-

tines, Levinthal and Marino, 2015). Nevertheless, it is fair to assume that any organizational adaptation reflects on various aspects of its internal dynamics as well as on its environmental positioning. It is the former that is of interest in this study.

One of the aspects that may be affected by macro organizational shifts are organizational tasks. The concept of “task” has long been studied in organizational research (Hackman, 1969; Wood, 1986). For the purpose of this paper we define a task as an abstract, manual, or repetitive procedure that calls for execution from an actor (e.g., Bosio and Cristini, 2018). From this perspective, a task is conditional on the *local* conditions that define its execution and that are specified by a sentient individual or by a team, and by the resources available. In other words, it is claimed that tasks are (a) enacted, meaning that they are inseparable from the individual that performs them (Hærem et al., 2015), and they are (b) a function of the context in which they are performed (e.g., Schatzki, 2005). The combination of these two elements implies that the resources employed to perform a task also serve a definitional function. Tasks are also classified in relation to their *complexity* that can be interpreted as the level of difficulty with which they are performed. This is, again, inseparable from context, resources, and individuals that deal with the task.

When an organization is moving from one setting to another to adapt to a particular environmental circumstance, one may expect that task numbers and complexity increases. The way in which the organization orients and structures the operations around tasks is considered part of the macro framework for this study. While organizations change and, for example, move from one set of routines to another, adjust their internal protocols and processes, or introduce new ones, they are challenging their internal dynamics. This has practical effects that could manifest in an increase of the number of tasks and/or in a re-definition of existing ones. Both elements challenge the status quo and require all workers to adapt to the changed circumstances. In other words, a re-definition of the level of complexity of the tasks in the organization should be matched with appropriate modes of cognitive plasticity (whether enacted and/or extended), such that these tasks can be performed to satisfaction. The model below puts this claim to the test.

## The Model

As anticipated, the research is performed through an ABM. Different from math-based simulations, ABM are computational in that they require a code to instruct a computer to perform specific operations (Fioretti, 2013). The code usually programs possibly heterogeneous *agents* that are attributed an indefinite number of characteristics and act autonomously. They are usually located in a space, defined as an *environment*, and this is also described by characteristics (for specifications of organizational environments, see Fioretti, 2013; Secchi, 2015; Secchi and Neumann, 2016). Agents operate in the environment through sets of *rules* that can be made to be interpreted or applied conditionally to events, situations, contexts, or other rules. An agent can be anything, from an abstract object such as an idea, to a person, or a country.

In this paper, we are concerned with the cognitive strategies that individuals and groups put in place to attune and cope with an environment that is changing abruptly (i.e. a plastic organizational environment). One may refer to this process in terms of adaptation. Although adaptation is something that could be, and has been, studied empirically (e.g., studies of adaptive performance, Jundt et al., 2015), no research has been conducted specifically on the attunement of cognitive to organizational plasticity.

The evidence gathered through this model will be simulated data, generated by the model IOP 2.0, and performed on the software NetLogo 6.1 (Wilensky, 1999). To make sure

all the passages in this model are accurately presented, the ODD protocol (Overview, Design concepts, Details) (Polhill, 2010) has been followed. Full description of the model is presented in the supplementary materials, available online.<sup>1</sup>

In two recent publications, Edmonds and colleagues discuss the importance of disclosing the *purpose* of an ABM (Edmonds et al., 2019). This may range from prediction, explanation, description, theoretical exploration, to illustration, analogy, and social learning. With this ABM, the purpose is to *explore* which cognitive characteristics are best suited to cope with a variety of challenging environmental circumstances to inform empirical research together with suitable HRM practices.

### *Agents and parameters*<sup>2</sup>

The model has three different types of agents: (a) employees, (b) tasks, and (c) resources. Each one of them has a set of characteristics, behaviors and rules that are described in Table 1. All the three agents are randomly located in an environment that represents an organization. However, location is not intended as physical distance, rather it is a functional situational proximity that makes resources available to employees for the purpose of performing tasks (Secchi, 2015). To make the simulation more realistic, employees have limited access to resources, depending on both location and other characteristics (see below).

**Employees.** These agents perform tasks by using available resources and, to do so, they are described by four characteristics, some of which have been used as parameters for the simulation. The first is *competence*  $c$ , distributed normally at random in the population, with a fixed standard deviation of 0.5 and a mean that could take any value between 1 and 2. Competence is to be intended as task-specific knowledge — e.g., an employee knows how a specific accounting software works. The second characteristic is the *ability*  $a$  to put knowledge into practice when performing a task — e.g., even though an employee knows a particular accounting software, it may have not used it for a while hence lack the ability to make it work here-and-now. Similarly to the previous parameter, the random normal distribution has a fixed standard deviation of 0.25 and a mean that is allowed to move between 0.5 and 1.5 (see Table 1). Various aspects such as these two usually appear in simulation work (for one of the latest examples, see Wall, 2018). *Role*  $R$  is another characteristic and it is set to give access to resources. It can be intended to mimic managerial roles in the organization;  $R = 1$  means that all possible resources are available to that employee. Hierarchy is something that features frequently in organizational ABM (e.g., Fioretti and Lomi, 2010). Finally, every employee is *docile*  $d$  to some extent ( $\approx \mathcal{N}(1, 0.5)$ ). Those with  $d > 1$  are more likely to use knowledge  $c$  of other employees when performing a task. To study what happens when this feature is present, the simulation has a switch — called *docility enabler* — that can be turned ON and OFF (in a way similar to what modeled in Secchi and Gullekson, 2016).

**Tasks.** Each task has a *difficulty*  $\delta$  level, allocated by a uniform distribution with a lower-bound limit. In the benchmark case, the difficulty ranges between 0 and 1, where the latter represents tasks that may potentially be more challenging, depending on characteristics of resources and employees (i.e. the situated *complexity* of a task seen above; see also Wall, 2018). To represent organizations where tasks are, on average, more difficult, the lower bound of the distribution may take the value 0.8. The other characteristic for tasks is *time*  $T_t$ . This is also allocated according to a uniform distribution function and it ranges between the integers  $[0, 4]$ . Every time an employee is set to perform the task, a clock starts ticking, indicating the time that is left to perform. When time expires and the task has not been completed, it relocates.

Table 1: Parameter Notations, Values and Descriptions

Parameter	Notation	Values	Test <sup>†</sup>	Description
<i>Setup conditions</i>				
steps	–	300		The measure for time in the simulation, the value indicates the upper value at which the simulation stops. Each step represents the attempt that an employee makes to find or perform a task.
number of employees	$N_e$	200		Number of employees $e$ in the organization; this is kept constant throughout the simulation.
proportion of tasks*	$P_{t,0}$	$\{x + 0.5 \mid 0.5 \leq x \leq 2\}$	{0.5, 2.0}	Tasks $t$ in the organization at time zero 0, expressed as a proportion $P$ of $N_e$ , such that the number of tasks $t = P_{t,0} \times N_e$ .
proportion of resources*	$P_{r,0}$	$\{x + 0.5 \mid 0.5 \leq x \leq 2\}$	{0.5, 1.0, 2.0}	As for the tasks $t$ , resources $r$ in the organization at time zero 0 are also $t = P_{r,0} \times N_e$ .
<i>Employee characteristics</i>				
competence	$c$	$\approx \mathcal{N}(\{x + 0.5 \mid 0.5 \leq x \leq 2\}, 0.5)$	1.0	Each employee has some knowledge related to task performance, distributed random normally, with a fixed standard deviation 0.5 and a mean that can take three values.
ability	$a$	$\approx \mathcal{N}(\{0.05, 0.1, 0.2\}, 0.25)$	{0.05, 2.0}	This is the expertise with which employees use their knowledge; it is distributed random normally, with a fixed standard deviation 0.5 and a mean that can take three values.
role	$R$	{0, 1}		The role gives access to different categories of resources (see below). Employees are randomly assigned to the two values.
docility	$d$	$\approx \mathcal{N}(1, 0.5)$		The extent to which an employee uses the competence $c$ coming from others to perform a task.
<i>Task characteristics</i>				
difficulty	$\delta$	$\approx R\{0, 0.4, 0.8\}, 1$	{0, 0.4, 0.8}	Tasks have a difficulty $\delta$ level that is attributed randomly, with a uniform distribution that ranges between the three values of $\delta_{min}$ and an upper bound of $\delta_{max} = 1$ .
time	$T_t$	$\{T_t \in \mathbb{N} \mid 0 \leq T_t \leq 4\}$		Initially attributed as a random integer to all tasks, when at least one employee is working on the task, $T_t$ decreases of 0.1 at every step.
<i>Resource characteristics</i>				
dimensions	$K$	{0, 1, 2}		When dimension $K = 2$ , a resource can be used to work on any task independent of its difficulty, but only highly competent employees would have the know-how to use such a resource. Various limitations operate when $K < 2$ .
proportion availability	$P_A$	{0.25, 0.5}	0.5	The parameter $A = 0$ when unavailable and 1 if available. The proportion of resources in the system that are available $P_A$ to employees with role $R = 0$ varies between {0.25, 0.5}. All resources are always available for employees with $R = 1$ .
immediateness	$I$	$\approx \mathcal{N}(\{-0.5, 0, 0.5\}, 0.5)$	{-0.5, 0.5}	This parameter is the extent to which a resource can be used, when $A = 1$ . When $I < 0$ then it takes time for the employee to utilize that resource. Immediateness increases with ability $a$ .
<i>Procedural parameters</i>				
docility enabler	$d_{en}$	{OFF, ON}	{OFF, ON}	When $d_{en} = 1$ then employees with docility higher than the mean of docility of employees ( $d > \bar{d}$ ), connect to other employees and use their ability to perform tasks.
extended cognition	$EC$	{OFF, ON}	{OFF, ON}	When activated, $EC$ makes individuals use a resource again and again if it has been successful in the past.
tasks waves hit	$t_w$	{0, 0.1, 0.2}	{0, 0.1, 0.2}	Every 10 seconds, $t_w$ percent tasks are added to the system. The percentage is calculated on the initial number of tasks $t = P_{t,0} \times N_e$ .
competence increase	$\Delta c$	{0.2, 0.4, 0.6}	0.4	Competence $c$ increases of a value specified by the parameter $\Delta c$ when a task is performed successfully.
ability increment	$\Delta A$	{0.1, 0.2, 0.3}	0.2	When $d_{en} = 1$ employees with $d > \bar{d}$ who complete a task receive an increase in their ability that equals $\Delta A$ .

Note. \* The math notation here means that the proportion moves in the range described at intervals of 0.5; † The test value is specified only when the parameter is allowed to change or became fixed in the experimental conditions. Notice that some parameters, such as  $d$  is distributed normally at random across agents.

**Resources.** There are three characteristics each of these agent is equipped with. They have a *dimension*  $K$  that ranges between 0, 1 and 2 and is allocated uniformly at random. A resource with  $K = 0$  is available to any employee and it can only be used to perform tasks with difficulty  $\delta \leq 0.25$ . On the other end of the spectrum, when  $K = 2$ , only highly competent employees with  $c > (\bar{c} + \sigma_c)$  — where  $\bar{c}$  is the mean and  $\sigma_c$  is the standard deviation of competence — can use it to perform any task, independent of difficulty  $\delta$ . The case in which  $K = 1$  is such that they can only be used with those tasks where  $\delta \leq 0.75$  by employees with  $c > (\bar{c} - \sigma_c)$ . This aspect is somehow traditional in ABM research on tasks (e.g., Herath et al., 2017; Fioretti and Lomi, 2010). However, not all resources are available to all employees. In fact, employees with role  $R = 1$  access all resources while those with  $R = 0$  only access resources with

*availability*  $A = 1$ . The proportion of resources available  $P_A$  to employees with  $R = 0$  can be 0.25 or 0.50. Another characteristic for resources is immediateness  $I$ . Available resources can be used straight away or they may take time before they are of use to an employee.  $I$  is distributed normally at random among resources, with a fixed standard deviation and a mean that could take the values  $\{-0.5, 0, 0.5\}$ . This latter element is a novelty of this simulation and, to the knowledge of the author, is seldom included in ABM.

The model has additional parameters that define the different processes (see below). As already mentioned, there is a *docility enabler*,  $\{\text{ON}, \text{OFF}\}$ , that is used to form teams and allows employees to use other employee's competence  $c$ , depending on own levels of *docility* — i.e. when  $d > \bar{d}$ , with  $\bar{d}$  being the mean *docility*. The switch also determines that the ability of employees increases as a function of the ability of team members:  $A = A + \frac{\Delta A \times \bar{A}_{tm}}{\sigma_{A_{tm}}}$ , where  $\Delta A$  is the ability increment that can take values  $\{0.1, 0.2, 0.3\}$ ,  $\bar{A}_{tm}$  is the mean ability of team members, and  $\sigma_{A_{tm}}$  is the standard deviation of team members' ability.

While the parameter above should take care of *enacted cognition*, an *extended cognition* parameter  $\{\text{ON}, \text{OFF}\}$  ties employees to resources that have been successfully utilized in dealings with tasks. The idea behind this is that successful cognitive extensions are resources for employees and, for that reason, they are preferred over others. Recent simulation of SEC can be found in Secchi and Cowley (2018).

As a way to mimic *plastic* organizational change, tasks are added to the existing pool, at regular intervals. While the simulation follows its own time, set by *steps*, the wave follows actual time, counting from the start of the simulation.<sup>3</sup> This means that the number of steps performed every 10 seconds is variable, because it depends from how “busy” employees are. Hence, the variability of time (*when* the hit wave comes) and the unpredictability of their location on the organizational environment (*where* it happens) mimic an organization's plastic adaptation to uncertainty and change. Organizational change may be reflected in a different and higher number of tasks that employees need to perform to bring the organization in a different position. The new tasks that come into the system could be  $\{0, 0.1, \text{ or } 0.2\} \times P_{t,0} \cdot N_e$ .

When an employee successfully performs a task, this disappears from the system and, at the same time, there is a *competence increase*  $\Delta c$  that is proportional to the difficulty  $d$  of the task performed.  $\Delta c$  can take three values,  $\{0.2, 0.4, 0.6\}$ , and the increment is in full — i.e.  $c + \Delta c$  — when tasks performed have  $d > 0.75$ , it is  $c + \Delta c/2$  when  $0.25 < d \leq 0.75$ , and it is  $c + \Delta c/10$  when  $d \leq 0.25$ .

While the simulation introduces employees, resources, and tasks and models them taking an individual (micro) perspective, both the conditions for interaction, together with the initial settings and the procedures (described below) identify the organizational (macro) framework. Not only conditions apply to the entirety of agents in the simulation, but stochasticity is such that it allows for emergence to be observed only at the systemic (organizational) level (Grimm et al., 2010).

### Process overview

The starting point of the simulation is the random location in which all three types of agents are placed in the environment. While employees and resources move following a random direction, tasks do not. This is done to mimic the relative stability of tasks, that are there to be performed. Every employee searches for tasks around, on a range  $\delta$  that is defined by the *proximity* constant.<sup>4</sup> Once found, the employee links to the task and to the resources available

in that same range. At this point, unavailable resources  $A = 0$  sever their links with low-rank employees with  $R = 0$ .

Task performance unfolds in two steps: (a) qualification and (b) action. The first step involves an assessment by each employee that defines whether a task can be performed or not. Competence and resource dimensions are matched to the difficulty of the task, according to the pseudo code:

```

if
  resource dimension = {2, 1, or 0}
  AND employee competence is, respectively =  $\{\bar{c} + \sigma_c, > \bar{c} - \sigma_c, \text{ or } > 0\}$ 
  AND task difficulty is, respectively =  $\{> 0, \leq 0.75, \text{ or } \leq 0.25\}$ 
then
  set task [qualified]

```

Once a task is qualified, then it could be acted upon by the employee. However, there are additional conditions that apply here. In fact, a task is performed and disappears from the system straight away only if the resource's immediateness is positive — meaning it is ready to use — and the employee ability can set the resource into use. This latter is exemplified by the product of ability and immediateness,  $A \times I$  (action, in the pseudo-code below). If  $AI > \delta$  then the task is performed to its completion. When these conditions are not met, then the task is not fully performed and/or the employee works through its own ability in an attempt to make the resource available. The pseudo-code below exemplifies this procedure:

```

if
  task qualification = 1 AND resource immediateness > 0
then
  set employee action [employee ability × resource immediateness]
  if
    employee action > task difficulty
    ask task [ disappear ]
if
  task qualification = 1 AND resource immediateness ≤ 0
then
  set resource immediateness [immediateness × (1 + employee ability/10)]

```

## Procedures and results

The section is organized as follows. First, calibration procedures and results are presented, then findings of the main simulation are introduced and discussed. All simulations were performed using Abacus 2.0, the supercomputer of the Danish e-Infrastructure Cooperation (DeiC) National HPC Centre, University of Southern Denmark.

### Calibration

The first approach to the simulation entails calibration of the parameter values (e.g., Boero and Squazzoni, 2005). This is particularly important, especially in the case of an ABM such as this one, where the stochastic component is modeled prominently in the code. The goal of a calibration procedure is twofold. On the one hand, there is a need to determine, for each parameter, which values do not affect the outcome variable (number of tasks performed,  $T_p$ ) in a way that is different enough from other values. On the other hand, the procedure checks

whether a parameter should vary at all. As indicated in a recent article (Seri et al., 2020), there is no consensus among scholars on how to achieve these two goals and on the most appropriate statistical technique to choose. In this article, parameters in the simulation are calibrated through means of a *sensitivity analysis* (Broeke et al., 2016).

The configurations of parameters are indicated in Table 1 and they can be summarized in a factorial design of  $4^3 \times 3^6 \times 2^3 = 373,248$  simulation runs. Due to the stochastic component of the simulation, there is a possibility that one run would not be informative enough. To avoid such an issue, power analysis was performed with the specifications suggested in Seri and Secchi (2017)<sup>5</sup>. Results indicated that one run was, in this case, enough due to the large number of configurations. The supercomputer Abacus 2.0 still took 4 days, 4 hours, 19 minutes and 23 seconds to perform the simulations.

Once data were downloaded onto R — a software for statistical computing — OLS regressions were performed per each variation of parameters, keeping the others constant. For example, when analyzing the `proportion of tasks`, there were four initial setup values, 0.5, 1.0, 1.5, and 2.0. Each one of those values was held constant in a regression model where the other parameters vary and repeated as many times as necessary to map the full range of configurations.

By keeping the first configuration ( $d_{en} = \text{ON}$ ,  $EC = \text{ON}$ , and  $t_w = 0$ ) as a benchmark, regression models are evaluated using  $R^2$  differentials to assess how much variation is due to the modification of the value of one single parameter. When necessary, variation in size of the  $\beta$  coefficients between regression models was also assessed. The result of this procedure led to the determination of the parameter values for the main simulation (column ‘Test’ in Table 1).

### Findings

The parameter values determined through the calibration procedure were inputted in a new simulation model, specified as a factorial design of  $3^3 \times 2^5 = 864$  runs. Again, there was the need to understand how many times these simulations should be performed on the supercomputer Abacus 2.0. Following a procedure similar to the one above (Seri and Secchi, 2017), the square root of the regression’s effect size, derived as a function of  $R^2$ , allowed a calculation based on an  $F$  test, indicating that 2 runs per configuration of parameters were necessary.

The first set of results is concerned with the efficiency of task performance. Employees in the system consider a number of tasks. Depending on the conditions outlined above (e.g., ability, competence, immediateness, and difficulty) some tasks are performed at the time they are considered, but not all of them. In fact, an efficient system would be one where employees always perform the tasks they take on. But such a system is also highly unrealistic, hence the split between tasks considered and those performed. A snapshot of this is visible in Figure 1, where the  $x$ -axis measures tasks considered while the  $y$ -axis is for those performed. The number of tasks in the system at the beginning of the simulation is set to its maximum ( $P_{t,0} = 2$ ), while the system is closed and no new tasks appear over time ( $t_w = 0$ ), such that those performed simply disappear. Also, `docility enabler` has been set to OFF, just to make the employees behave as they usually do in standard classic individualistic approaches. A condition that makes the difference in this case is the mean `immediateness`, the variation of which determines an increase in the number of tasks performed. Figure 1 also shows the differences when more `resources` are available in the system ( $P_{r,0} = 0.5, 1.0, 2.0$ ) and when extended cognition  $EC$  is turned ON and OFF.

As expected, an increase in the number of resources move the data slightly to the right (i.e. more tasks are considered) and more strongly to the upper side of the plot (i.e. more



tasks are performed).  $EC$  serves as a contraction in efficiency, at least, if considered at face value. Both plots shall be read on the basis of what happens around their diagonal. This represents an equilibrium where most tasks considered are performed to completion. When data appears below the diagonal, then more tasks are considered than performed; instead, when data is found above the diagonal, more tasks are performed than considered. This is controlled by the parameter `immediateness` such that the shift is very clear in these two plots, with data moving from the lower right part in the first figure ( $\bar{I} = -0.5$ ) to the upper left part in the second figure ( $\bar{I} = 0.5$ ). The behavior of employees when  $EC = ON$  is such that fewer tasks are performed, but there seems to be an “efficiency equilibrium”, meaning that most tasks considered are also performed, and this indicates employees show some *stickiness* to a task — i.e. they stay attached to a task until performed. Since  $EC$  ties the agent-employee to resources, and it is interesting to notice that this has an effect on tasks. In the cases when  $EC = OFF$ , employees move more freely around tasks, leaving those appearing more difficult and performing those immediately solvable. The first can be called a *concentration strategy*, where some employees focus on some tasks only, perhaps the most relevant ones. The second is a *differentiation strategy*, in which quantity of tasks solved takes priority over those that are more time consuming. Both are viable strategies, the question is when is one more effective than the other.

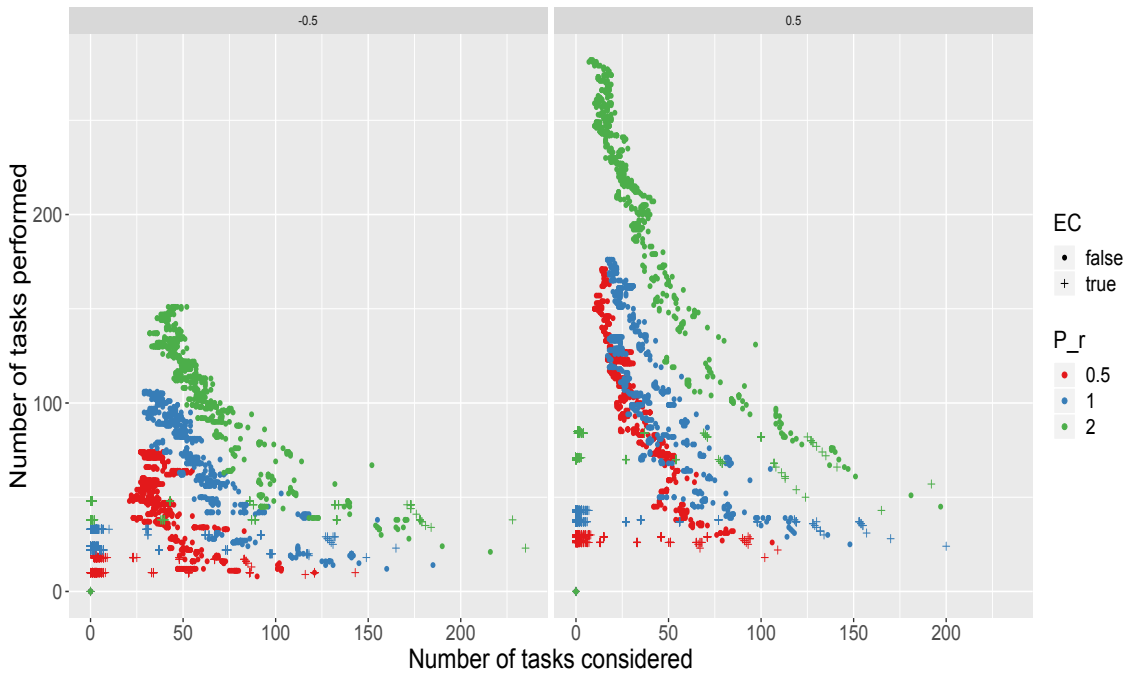


Figure 1: Number of tasks performed and considered, analyzed by mean immediateness  $\bar{I}$  (split panes), extended cognition  $EC$ , and proportion of resources  $P_{r,0}$  (setting:  $P_{t,0} = 2$ ,  $d_{en} = \text{false}$ ,  $\delta_m = 0$ ,  $\bar{a} = 0.05$ ,  $t_w = 0$ )

The parameter `hit waves`  $t_w = 0.2$  is an attempt to find an answer. This setting represents a highly challenging environment in which the organization is in. Figure 2 presents data with `docility enabler = ON`, allowing employees to work together and utilize each other’s competences. The three panes show different patterns when the difficulty of tasks increases ( $\delta_m = 0, 0.4, 0.8$ ). The two axes are the same as in Figure 1. Here too,  $EC$  poses a constraint on the number of tasks handled and performed, and concentrates operations around

the diagonal at the bottom left part of the quadrant (as shown in the zoomed image). Not being attached to particular resources (i.e.  $EC = \text{OFF}$ ) seem to increase the likelihood to perform tasks, hence indicating that a *differentiation strategy* is better when it comes to conditions of extreme change/plasticity. Of course, as mean difficulty ( $\bar{\delta}$ ) increases as seen by  $\delta_m = 0.8$  (right pane, Figure 2), fewer tasks are performed, making a *concentration strategy* (see the zoomed image;  $EC = \text{ON}$ ) particularly apt to those circumstances instead.

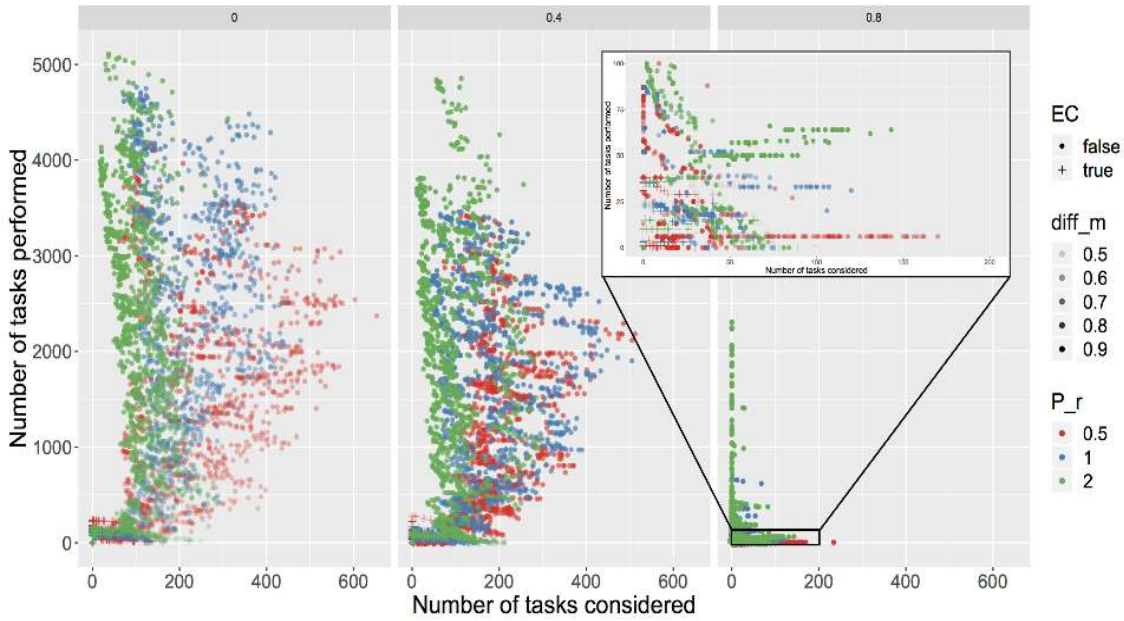


Figure 2: Number of tasks performed and considered, analyzed by min difficulty  $\delta_m$  (split panes), extended cognition  $EC$ , proportion of resources  $P_{r,0}$ , and mean difficulty  $\bar{\delta}$  (setting:  $P_{t,0} = 2$ ,  $d_{en} = \text{true}$ ,  $\bar{a} = 0.05$ ,  $t_w = 0.2$ )

For the next set of results, a different outcome variable is considered: the raw number of tasks performed divided by the number of tasks considered. This is the *task efficiency ratio*  $E_t$ , and it varies between 0 and 1 for  $\approx 77\%$  of the observations, going up to 5 for another  $\approx 22\%$ . As we already know from the immediacy parameter as described above,  $E_t > 1$  derives from the fact that some tasks are performed at the same time they are considered. The higher this ratio  $E_t$ , the more efficient the employees are in performing their tasks.

In Figure 3, the task efficiency ratio  $E_t$  is on the  $y$ -axis<sup>6</sup> while the  $x$ -axis measures mean difficulty of tasks. From the three plots, the initial conditions for task difficulty  $\delta_m$  are clearly visible, since most tasks performed start close to the midpoint between the minimum value  $\delta_m$  and the maximum, that is always 1. A first observation is that most tasks are performed when  $E_t < 3$ , with the cloud of points moving towards this upper bound of 3 as the waves of tasks increase. This is visible when we move from the left ( $t_w = 0$ ) to the right ( $t_w = 0.2$ ) pane in Figure 3.

As already seen above, most tasks are performed, on average, when teamwork is made possible (i.e. docility enabler,  $d_{en} = \text{ON}$ ). Figure 3 indicates that this is also the most efficient condition, since there is a higher percentage of existing tasks performed with  $E_t > 1$  (see the position of the + signs on the plot). From the same Figure 3, it is also apparent that the effect is more relevant when difficulty increases, especially when  $\bar{\delta} = 0.9$ .

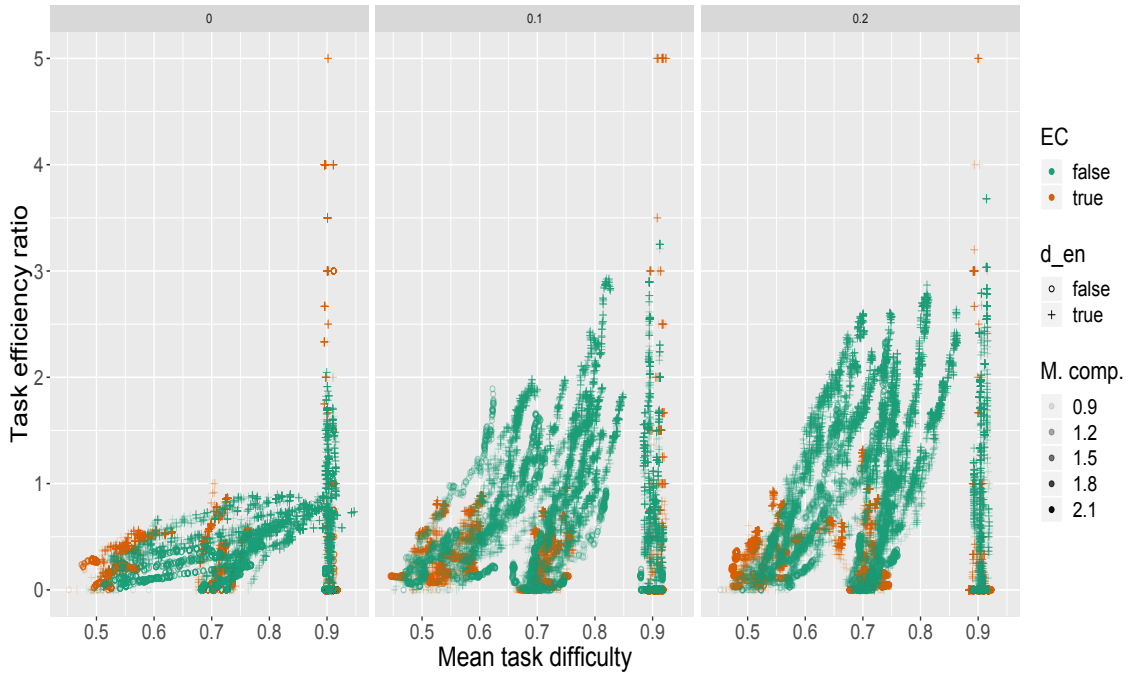


Figure 3: Task efficiency ratio per mean difficulty, analyzed by hit waves  $t_w$  (split panes), docility enabler  $d_{en}$ , extended cognition  $EC$ , and mean competence  $\bar{c}$  (setting:  $P_{t,0} = 0.5, P_{r,0} = 0.5$ )

Another pattern that is discernible from Figure 3 relates to the condition when extended cognition  $EC = OFF$  (green color on the plot), showing that re-use of the same resource does not seem to bring gains in terms of efficiency  $E_t$ . This result is consistent with the ones above. However, we can now appreciate that turning  $EC = ON$  allows the organization to enable outstanding performance. In fact, with very limited exceptions, only docility-enabled employees operating under  $EC$  conditions are visible when  $E_t > 3$ . Finally, Figure 3 also describes the data in relation to the mean competence  $\bar{c}$  of employees. Fading colors indicate a decrease of competence, on average, in the system. The three panes show that competence is much needed when mean difficulty goes up while it mostly fades when  $E_t < 1.0$ . As employees get more efficient in their performances, they need higher levels of competence to accomplish their goals. An interesting trend here is that  $d_{en}$  seems to be associated with a better use of competence, especially on the central and right panes.

### Implications and conclusions

The objective of the simulation and of paper is to explore the strategies with which individual and group's *cognitive plasticity* can attune with *organizational plasticity* (Herath, 2019; Levinthal and Marino, 2015). The ABM IOP 2.0 has created an organizational environment (the macro framework) that compared different degrees of cognitively challenging situations, where tasks either become more difficult and they increase at high rates. In these conditions, employees are tested by implementing various combinations of different cognitive “modes”, one that is centered on the use of resources and the other that on cooperation with colleagues. The first reflects aspects of *extended cognition* (Menary, 2010a), while the second represents *enacted cognition* (Magnani, 2007), especially docile processes (Simon, 1993; Secchi and Bar-

done, 2009).

One of the most relevant results is that *competence sharing* is a cognitively effective strategy. Simulation results indicate that *docility* helps employees cope with plasticity especially when the number of tasks increase. In light of the way in which results tie micro elements with the macro framework, suitable HRM strategies may include the following:

- (a) The data from Figure 3 indicates that competence is key to face an increasing number of tasks, hence proactive mapping of competences becomes essential to face organizational plasticity.
- (b) Another implication that comes out from a combination of results from Figure 2 and Figure 3 is the central role of *docility* as a cognitive approach to enable competencies to become an organizational resource. In other words, it is the sharing of competence that makes it a core resource, not the high level of competence per se. HRM should train management how to isolate and assess docility-based behavior.
- (c) Figure 2 suggests that cooperation is supported by the way in which resources are shared in a team and in association with task performance. A strategic positioning of HRM would be that of assessing the availability of resources for organizational teams and designing a (physical and social) environment that makes it easier to share them.

Another finding concerns the *exploitation of all sorts of external cognitive resources*, resulting in an efficient strategy. Under particularly demanding conditions, the use of resources and the combination of competencies allow a selected number of employees to perform higher numbers of difficult tasks. HRM strategies, mostly based on Figure 3, may support this behavior through:

- (a) designing excellence programs aimed at isolating those employees who are (or have been) outperforming others, especially in terms of task complexity handling;
- (b) helping managers to assign these focused employees to those tasks that require highly specialized (i.e. competent and highly docile) individuals to be performed;
- (c) training management on how to detect and encourage externalization and enactment cognitive strategies, such that they can be employed more widely when task complexity increases.

#### *Concluding remarks and directions for future research*

This paper has for the first time presented a description of some of the mechanisms that connect micro cognitive and macro organizational (task-related) aspects of plasticity. Results from the ABM indicate that different cognitive strategies may be employed to cope with organizational plasticity, some of the most effective include active exploitation of competencies and other resources. The role of HRM is determinant, in that it may work as an enabler of cognitive plasticity by ensuring that the conditions necessary to manage a possibly overwhelming number of tasks are in place.

Future research could take three directions. One would be that of validating the IOP 2.0 Model with empirical data while the other is to explore whether other aspects of the SEC perspective become relevant for plasticity, and isolate strategies other than the two introduced above. Another promising line of research is that of factoring in HRM (either in a new version of the IOP 2.0 Model or in an empirical study), and assess which action would more effectively enhance a *differentiation* or a *concentration* strategy.

**Notes**

<sup>1</sup>The file will be available on the platform OpenABM, after peer review; both the model and the supplementary files materials are available for peer review here: <https://www.comses.net/codebases/4ff566a6-c0f8-4ca2-aa5releases/2.1.2/>.

<sup>2</sup>A parameter that is allowed to vary in the simulation is indicated in the text with `teletype font`.

<sup>3</sup>This happens, actually, around the start, and precisely when `step/tick= 10`.

<sup>4</sup>Proximity is kept constant in this simulation but it can be made to vary, as usually happens in ABM (e.g., Secchi and Gullekson, 2016; Bardone and Secchi, 2017).

<sup>5</sup>These are  $\alpha = 0.01, 1 - \beta = 0.95$ .

<sup>6</sup>The plot has been cut to  $E_t \leq 5$  because almost 99% of data points fall below that threshold for all three  $t_w$  conditions.

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