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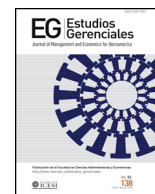
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Article

Representation of unlearning in the innovation systems: A proposal from agent-based modeling



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ABSTRACT

In the present work it is understood the unlearning as the voluntary effort made by firms to abandon the capacities that are not necessary to compete in an innovation system. Modeling and simulating unlearning makes it possible to know emerging behaviors resulting not only from learning, but also from agents unlearning who try to adapt to other agents and the competitive environment. The objective of this work is to represent and analyze the unlearning from the agent-based methodology. As conclusion, a model representing unlearning as a negative variation in capacities accumulation was obtained, which according to its speed, has a different impact on the performance of the innovation system.

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Representación del des-aprendizaje en los sistemas de innovación: una propuesta desde la modelación basada en agentes

RESUMEN

En el presente trabajo se entiende el desaprendizaje como el esfuerzo voluntario que las firmas realizan para abandonar las capacidades que ya no son necesarias para competir en un sistema de innovación. El modelar y simular el desaprendizaje, permite conocer comportamientos emergentes producto no solo del aprendizaje, sino también del desaprendizaje de los agentes al intentar adaptarse a otros agentes y a su entorno competitivo. El objetivo de este trabajo es representar y analizar el desaprendizaje desde la metodología de la modelación basada en agentes. Como conclusión se obtuvo un modelo que representa el desaprendizaje como una variación negativa en la acumulación de las capacidades, que de acuerdo a su velocidad, tiene diferente incidencia en el desempeño del sistema de innovación.

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Representação do desaprender em sistemas de inovação: uma proposta a partir dos modelos baseados em agentes

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No presente trabalho, entendemos o desaprender, como o esforço voluntário que as empresas fazem para abandonar as capacidades que já não são necessárias para competir em um sistema de inovação. Modelar e simular o fato de desaprender, permite conhecer os comportamentos emergentes, não só da aprendizagem, mas também do desaprender dos agentes ao tentar se adaptar a outros agentes e ao ambiente competitivo. O objetivo deste trabalho é representar e analisar o desaprender a partir da metodologia da modelagem baseada em agentes. Como conclusão, obteve-se um modelo que representa o desaprender como uma variação negativa na acumulação das capacidades, que de acordo com sua velocidade, tem uma incidência diferente no desempenho do sistema de inovação.

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1. Introduction

The innovation systems literature highlights knowledge, learning, and innovation as important factors for global competitiveness in a knowledge-based economy (Lundvall, 1992; Organization for Economic Co-operation and Development – OECD, 2000). However, the deterioration and retention of the knowledge base of organizations require particular attention, as firms not only acquire new knowledge and learn as a product of their interaction, but they also discard some of this knowledge voluntarily, bringing to light the phenomenon of unlearning. Similarly, literature has acknowledged that routines and old practices that are intentionally lost play a crucial role when it comes to deciding what the organization unlearns and learns. Unlearning as a break from the inertia of past learning in relation to the environment (Hannan & Freeman, 1984), is understood in literature as a voluntary effort the organization makes to free itself from knowledge that is no longer necessary. This argument brings to light the fact that firms need to somehow unlearn routines and old practices in order to learn better and more adequate ways to do things. In other words, they must decide what capacities to accumulate and which ones to de-accumulate or not use.

On the other hand, some researchers have argued that firms may forget accidentally, i.e., knowledge may be lost with no explicit wish to eliminate it from the organization. Many authors have documented how accumulated knowledge in an organization may dissipate rapidly and inadvertently (Argote, 1999; Argote, Beckman, & Epple, 1990; Darr, Argote, & Epple, 1995) and how that involuntary oblivion may have serious negative effects on productivity, profitability, and competitiveness (Argote, 1999). However, in the strategic context of organizations, unlearning occurs voluntarily, as organizations grow and become more complex, making it necessary to transform and readjust their formal structures, procedures, systems, routines, and processes in congruence with the dominating logic of the market in which they act and interact (Bettis, Wong, & Blettner, 2011).

From this perspective, then, unlearning may be considered a complex phenomenon that arises in an innovation systems (IS) along with learning. The fact that firms learn new and more appropriate ways to do things through the use and accumulation of their capacities somehow implies stopping the use and accumulation of some other capacities and old practices acquired before. From this perspective, then, we may ask ourselves how some regions and their agents unlearn. It is known that capacity of accumulation and deaccumulation enables organizations to adapt to the new requirements of the environment and to respond to innovation opportunities. However, traditional innovation system models have not represented clearly the complexity of the learning process,

let alone that of unlearning. Modeling and simulating unlearning makes it possible to know emerging behaviors that are product of the interaction or lack thereof between its agents and their environment.

Methodologically, the work is done in the following way, first are presented some main assumptions, with which the conceptual model and the logic of the simulation are elaborated. Then the simulation model is applied through the parameterization of the model and the simulation of scenarios that allow to experiment with different factors of unlearning, in order to analyze its incidence in the performance of the innovation system. This methodological approach is justified considering innovation systems as adaptive complex systems. The latter are conceived as an arrangement of interacting agents described by rules, which change as experience accumulates (Holland, 2004). These adaptive complex systems are represented recurrently through Agent-Based Modeling (ABM), since it is a powerful tool to obtain information on the dynamics of systems that are made up of heterogeneous agents and the relationship between them has its own characteristics (Rahmandad & Sterman, 2008), justifying the adoption of this approach to address the problem of representing unlearning in innovation systems.

This work aims at representing unlearning of an innovation system under the perspective of ABM. To this end, the section two establishes a theoretical framework as the first phase for the construction of the model. Through exploration, concepts and requirements of the system are captured, for example, unlearning, forgetting, innovation opportunities (understood as the demands of the environment of new products) and the characteristics of the agents, as well as decision rules for interaction. The section three is geared toward the analysis, design, and methodological construction of the model as second phase, with the conceptual model obtained as result. The third section presents the results of the previous phases and translated into a source code in the Netlogo v. 5.1.0 platform, in order to later verify the structure and behavior of the resulting computational model. The work ends with the analysis of the results and pertinent conclusions.

2. Theoretical framework

The different perspectives of innovation systems have been characterized by addressing top-down problems that are more typical of national innovation systems, leaving research under other perspectives, e.g., bottom-up perspectives (Howells, 1999; Iammarino, 2005; Uyarra, 2010). Conventional innovation system analysis methods, in particular those of regional innovation systems (RIS) and their different typologies, currently show difficulties when it comes to describing complex dynamics, such as innovation processes, where both learning, and unlearning are

presented, which is why it is necessary to use alternative analysis mechanisms such as computational simulations. The presence of simulation models that aim at researching innovation systems and their innovation processes, life for example, unlearning associated to learning, are scarce in literature. This is due to the fact that innovation as a social phenomenon is extremely complex (Robledo & Ceballos, 2008). However, researching these processes through modeling and simulation may help us know and understand better the behavior and performance patterns of agents in an innovation system. Agents are understood here as actors who make decisions in the innovation system, which can be explorers, intermediaries, exploiters or with combined capabilities of the previous ones, which will be introduced later.

The presence of the different learning models in specialized literature represents different dynamics of the processes intervening in innovation (Ahrweiler, Pyka, & Gilbert, 2004). Moreover, they have contributed to improving the comprehension of complex innovation and learning processes (Triulzi, Pyka, & Scholz, 2014). However, bounded rationality (Term coined by Simon (1957), which proposes that there are limits to rational behavior, especially he highlights imperfection of knowledge, uncertainty with respect to the consequences of our decisions and the limit in the imagination of people), which is a characteristic of these processes, is seldom considered when representing not only learning dynamics (Ponsiglione, Quinto, & Zollo, 2014) but also those of unlearning.

The perspective that argues that firms must unlearn their own practices in order to learn new ways of doing things implies, then, not only the creation of new capacities and knowledge, but also the elimination of those already existing (Martin de Holan & Phillips, 2004). In the same sense, Leal-Rodríguez, Eldridge, Roldán, Leal-Millán, and Ortega-Gutiérrez (2015), recognize unlearning, as fundamental to allow the accommodation of new knowledge in the firm, thus promoting innovation and therefore the best performance of the company. Unlearning, from this point of view, is positive; when a piece of knowledge is old and has not been renewed or updated in time, this could hinder the firm from the possibility of adapting to the new demands of the environment in which it competes, then unlearning is the solution. From an individual level, unlearning can be seen as the loss of influence of old knowledge on cognitive or behavioral processes (Grisold & Kaiser, 2017). According to Hedberg (1981) (who imported the term 'unlearning' from the psychology literature to management area (Howells & Scholderer, 2016)), unlearning is a necessary complement to the concept of organizational learning, and he sustains that "unlearning is different from learning; conceptually, it is necessary to understand how firms learn, because knowledge grows and becomes obsolete at the same time its reality changes" (Hedberg, 1981, p. 3). As a result, firms necessarily unlearn; that is, they become engaged in a process through which they discard some knowledge (Hedberg, 1981), which, having fallen in disuse, negatively affects the use and practice (deaccumulation) of some capacities that may not be necessary to innovate. Similarly, holding a capacity requires the use of resources of all kinds (Barney, 1991), so unlearning is essential to increase the efficiency of firms.

The process of reduction or elimination of pre-existing knowledge or habits, which otherwise represent formidable barriers to learning is defined by Newstrom (1983), as unlearning. Many researchers point out that the existence of unlearning is necessary for learning to occur. For example, Anand, Manz, and Glick (1998), point out that there are circumstances in which the existing memory may be more of an obstacle rather than an aid. Similarly, Crossan, Lane, and White (1999), argue that tension between the assimilation of new learning and the use of what has already been learned appears because learning has been institutionalized, hindering thus the assimilation of new learning: it is possible to relate this to the conformation and difficulty of changing routines, as

expressed in Cyert and March (1999). This approach is known as the behavioral learning approach, which is centered on the standard routines and operation processes in the organization.

Other authors, like Bettis and Prahalad (1995) and Miller (1993, 1994), have adopted a more cognitive vision regarding learning, arguing that not discarding or unlearning old dominant logics is one of the main reasons why firms find it so hard to adjust their behaviors to the new environmental conditions, even when the organization itself experiences and clearly shows the changes in the environment where it operates. This approach helps us understand the behavior of organizations in the environment where they move and compete. Another aspect to take into account is the culture, according to Leal-Rodríguez, Eldridge, Ariza-Montes, and Morales-Fernández (2015), not all cultures promote unlearning, in their work find that a culture focused on the market has a positive impact on both unlearning and innovation, this finding is consistent with the market pull approach that will be given to the model. In a complementary way, the work of Tsang (2017), recognize that unlearning should be management and is not simply a process of forgetting.

Innovative opportunities, understood as demands for innovations by the market, play a crucial role in organizations when it comes to adjusting behaviors related to new possible conditions of the environment. When a firm notices a market need and its difficulty to respond, it will try to diversify (even make a quick change in the business core). However, Bettis and Prahalad (1995) and Miller (1994) argue that it is not only a matter of routines, but also of the collective representations of the environment, which form different and alternative points of view that probably hinder it (bounded rationality), preventing members of the organization from interacting and capturing the current realities that are necessary for interpreting changes and understanding their consequences, without being unfamiliar with the stimuli of the environment (Kiesler & Sproull, 1982). Stimuli could be key when it comes to interpreting environmental changes and may be present in the demands understood as innovative opportunities. An innovative opportunity can be defined as the attributes of an innovation demanded by the market, which may be satisfied through the innovation capacities of competitor firms which, at the same time, seek a stimulus or reward from the system, these attributes are manifested by vectors in the simulation model; the reward given by the market is what motivates firms to innovate, which is to make big profits by impacting the market with new products, processes and novel market and organizational methods (Table 1). As a consequence, old dominant logics or mega-routines are one of the most important factors that prevent firms from discarding old knowledge, as a crucial part of organizational knowledge to be unlearned when circumstances demand so, since they are inherently adaptive properties of the firm, as long as the domain of application and environment do not change significantly (Bettis et al., 2011).

Dominant logics represent the cognitive vision of learning, which is seen as a lens that enables the organization and its members to understand collectively how to adequately respond to the environment in which they work. In short, companies that can unlearn and reformulate their past successes to adapt to changing environmental conditions and situations will have a higher probability of survival and adaptation in an innovation system. From this approach, unlearning is observed as a fundamental dimension for change, because, as Tsang and Zahra (2008) argue, unlearning refers to discarding old routines to give way to new ones. Unlearning is defined, then, as the process of eliminating or discarding knowledge (and its associated capacities) voluntarily as a strategic purpose, without necessarily creating new knowledge and/or capacities, although there is often a close relationship between these two. It is worth mentioning that capacities are not eliminated nor discarded so easily; for this, there must be a process in

Table 1

Comparative analysis of simulation approaches.

Simulation approach	Focus	Research questions	Key issues	Theoretical logic	Common experiments
System dynamics (Sastry, 1997; Sterman, Repenning, & Kofman, 1997)	Behavior of a complex system with causality and time measurement	What conditions create instability in the system?	Intersection system; causal loops; level accumulation; flows that specify system rates.	Entry description; loop-connected system; stocks and flows that produce the system's results.	Add causal loops; change of flow rates; change in the variation of flow rates
NK-type adaptive landscapes (Gavetti & Levinthal, 2000; Levinthal, 1997)	Adaptation speed and efficiency of modular systems vs. adaptation to an optimum point.	How long does it take to find the optimum point? What is the efficiency of the optimum point?	System of N nodes and K pairing; adaptive landscape mapping the performance of all combinations; adaptation by movements.	Modular adaptation to find the optimum point by (incremental movements and long jumps from the strategy)	Vary N and K; changes in adaptation adding landscape map; generate shocks in the medium.
Genetic algorithms (Goldberg, 1989; Holland, 1975; Holland & Miller, 1991)	Adaptation of an agent population via simple learning for an optimum form of the agent.	What affects the adaptation rate (learning and/or change)? When does an optimum form emerge?	Population of agents and genes; variation via mutation (errors) and crossing (recombination); selection through aptitude (performance); retention via copy of selected agents.	Optimization; adaptation of an agent population using an evolutionary process toward an optimum agent form. Variation, selection, and retention.	Variation in the probability of mutation and crossing and in evolution time; creation of environmental shocks.
Cellular automata (Lomi & Larsen, 1996; Von Neumann, 1979)	Macro models from micro interactions through spatial processes (diffusion, propagation, and competition) within a population.	How does the pattern and the change emerge? How fast does a pattern emerge? What is the (spatial) degree in which agents influence each other (distances) at which they are located?	Population of semi-intelligent organized agents; agents use rules (local and global) for interaction, some based on spatial processes; agent neighborhood where local rules are applied.	Description; interactions between agents follow rules that produce macro-level patterns.	Change in rules; change in neighborhood size.
Agent-Based Models (ABM) (Axelrod, 1997; Epstein & Axtell, 1996; Holland, 1975)	Macro-level emergence of behavior patterns in a system based on interactions of semi-intelligent agents at a micro level.	What are the effects of the behavior patterns in all systems? How fast does a pattern emerge and how does it evolve? How do agents adapt and learn?	Population; global variables, population properties; rules of decision-making for interaction; evolution; aggregation, adaptation, and learning. Collective intelligence and bounded rationality.	Description of agents, emergence from interaction or collaboration between agents; aggregation; non-linearity; flows and diversity; tags; internal models and construction blocks.	Change in rules; variation in characteristics (specialization) of agents and environment, variation of agents in time.

Source: Prepared by the authors based on Davis, Eisenhardt, and Bingham (2007).

which they are not used or practiced. We will call this unlearning by non-practice.

Contrary to the unlearning current, forgetting researchers emphasize the importance of not losing knowledge, and state that avoiding forgetting is crucially important to maintain levels of performance previously reached by the firm. This school of thought is particularly in disagreement with the theory and models of learning curves, which establish a positive relation between experience and productivity. Although studies on learning curves are generally limited to production adjustments, the theory has been extrapolated to other dimensions of organizational learning (Abernathy & Wayne, 1974). Such dimensions are: the cost of transition, refers to when costs cannot be reduced as fast as they were added through design changes; decay of innovation, when the company's strategy is disconnected from innovation; new technological developments, which can remove companies from the market if they are not updated; common elements of change, product, capital equipment and process technology, task characteristics and process structure, scale, material inputs and labor; risks of success, making it difficult to change routines that will no longer be successful; managing the technology, the technological change must be faced strategically.

In spite of the solid conclusions supporting learning curves in operation research (for a more detailed review see Argote et al. (1990) and Adler and Clark (1991)), involuntary loss of knowledge (forgetting) has been documented in studies of intermittent production for more than half a century. These suggest that in situations in which changes and other interruptions make cumulative production not seem continuous, learning as a result from experience is followed by forgetting and then by re-learning (Carlson & Rowe, 1976). Several researchers have begun to explore the important strategic consequences of these observations. However, this statement would go against past successful practices from firms, making it harder to lose capacities for innovation acquired long ago, and which have been significant for the firm. Such behavior does not present any relation with the routines that have been acquired by previous experience at the firms (Nelson & Winter, 1982). Finally, specialized literature suggests that unlearning is positive given the fact that it helps the organization to adapt to its environment, while forgetting is an organizational phenomenon that may have negative consequences. Besides, available research shows that even in the most formalized knowledge setting, knowledge retention and learning by doing (Arrow, 1962), are far from perfect and/or automatic. Therefore, other kinds of learning are set up, which complement it, e.g., learning by using (Rosenberg, 1982) and learning by interacting (Lundvall, 1992).

A great number of studies reported by literature about innovation systems present a static photo of agents and institutions instead of presenting adjustment processes and their dynamics, enabling longitudinal studies that take into consideration localized learning (Howells, 1999; Iammarino, 2005; Uyarra, 2010; Uyarra & Flanagan, 2010) and agent unlearning in an innovation system. According to Borrelli, Ponsiglione, Iandoli, and Zollo (2005), theoretical approach of the knowledge-based organization (Fransman, 1994), which considers that businesses are knowledge repositories (Penrose, 1959), as well as integrated specialized knowledge systems (Simon, 1961), capable of preserving and generating knowledge (Grant, 1996), are systems capable of learning by trial and error in the process (Herriot, Levinthal, & March, 1975), building and selecting routines (Nelson & Winter, 1982), may be of help to consider not only relations and interactions, but also to build a learning system.

Based on the functional social model of Parsons (1951) and the concept of organizational learning defined by Schwandt (1997, p. 3) as “[...] a system of actions, actors, symbols, and processes that enables an organization to transform information into valuable knowledge, which in turn increases its capacity for long-term

adaptation”, Zollo, Crescenzo, and Ponsiglione (2011), propose the components and characteristics of an RIS based on the learning system by Schwandt and Marquardt (2000). The components are four subsystems that characterize and schematize the agents of an RIS; these four subsystems provide an analytical framework for the description and evaluation of the dynamic functions of the organization's learning system; knowledge flows caused by interaction between agents give way to emerging behaviors of evolutionary character, such as an interactive learning of collective character (for more details, see Zollo et al. (2011)). On this basis, then, it is possible to define the competences of the four actors of an RIS: explorers, are responsible for generating new knowledge, such as centers and groups of research; exploiters, who are responsible for generating market value from the use of knowledge, especially firms; intermediaries, have the responsibility of connecting the agents that generate knowledge with those who use it, here are the centers of technological development and knowledge intensive business services, and regional government, which intervenes from programs that strengthen the use of science, technology and innovation, such as the pacts for innovation in Colombia.

Modeling and simulating the processes of innovation, learning, and particularly, unlearning, puts forward the need to describe relevant and important elements that influence agents and their innovation processes, such as, for instance, resources and capacities, as well as the level of competence of the agents in the system. Different approaches and definitions associated to the concept of capacities within the context of organizations have been addressed in literature; the most relevant include the concepts of technological capacity and innovative capacity. Lall (1992), makes it possible to reconstruct the evolution and distinguish the perspectives in regards to the concept of capacity; likewise, the perspective of resources (Barney, 1991; Penrose, 1959; Wernerfelt, 1984) and capacities are the cornerstone of the proposed model. Capacities are defined as the ability to make use of resources in order to carry out a task or activity (Hafeez, Zhang, & Malak, 2002). Another important element that influences not only interactive learning and unlearning in an innovation system are core competences; Hafeez et al. (2002), define these as the capacities that enable the company to deploy its resources so that they generate competitive advantage.

Coincided in the concept of organizational capacity by Renard and Saint-Amant (2003), Robledo, Gómez, and Restrepo (2009), propose a new redefinition of technological innovative capacities, such as the organizational capacities on which the organization enables the achievement of its strategic technological innovation objectives; likewise, they propose a categorization, classifying and defining the specific technological innovative capacities in five capacities: strategic direction capacity, R&D capacity, marketing capacity, production capacity and resource management capacity. From the aforementioned perspective, unlearning was modeled and simulated, taking into account the accumulation and deaccumulation of capacities through learning by doing and unlearning by not doing, as well as the interaction of heterogeneous agents in an innovation system.

The model seeks to describe unlearning from the concept of learning; the latter is defined as the dynamics in which, based on resources, the firm not only accumulates capacities, and therefore, core competences (Robledo, 2013), but also deaccumulates capacities, breaking the inertia of past learning in relation to the means or environment. The decision of using innovative capacities in the model has a purpose, which is the firm's ability to carry out organizational functions and achieve its innovation results through the deployment, combination, and coordination of organizational components according to the strategic innovative goals previously defined by the firm or agent.

The dynamics of learning and unlearning are presented through rules of decision-making, which are defined as the behavior

(search for agents such as proximity and complementary partners and eventual establishment of alliances) for which interactions between agents happen in an innovation system. Interactions occur through two mechanisms or rules of decision-making: the first one is called localization distance or relational proximity distance between agents, defined as the shortest relational distance separating agents for their interactions. The second rule is called distance of complementarity in capacities, defined as the shortest distance between the level of the innovative capacities of the agents; for example, if the capacity level of an agent is lower than the level of attribute of innovation demanded by the market, the agent will seek a partner capable of fulfilling said level of capacity, which could be called satisfaction of the market or environment demand. This procedure is what generally generates multiple mechanisms to make up labor division and productive chains in innovation system.

3. Design and methodological construction model

At present, literature specialized in business management presents a growing interest in simulation as a methodological approximation to theoretical development in topics related to strategy and organizations (Robledo, 2013), since simulation reveals the results of interaction between multiple organizational and strategic processes developed throughout time (Davis, Eisenhardt, & Bingham, 2007). Modeling and simulation are appropriate methods for understanding complex systems where time dynamics are important. Table 1 describes a comparative analysis of the different simulation approaches, and ABMs are added as a complement. The objective of ABMs is to enrich the knowledge of processes that may appear in a great variety of applications but do not provide a precise representation of an empirical process (Axelrod & Tesfatsion, 2006). ABMs study the macro-level emergence of behavior patterns in a system based on interactions of semi-intelligent agents at a micro level. Information and knowledge of the agents regarding other agents and the environment are limited. The agents may collaborate, compete, coordinate, share, and interact amongst each other, as well as with the environment in which they work.

The proposed model is based on doctoral thesis research work, socialized and disseminated by Quintero and Robledo (2012, 2013) and Quintero, Ruiz, and Robledo (2016) about “*Learning in regional innovation systems: an agent-based model*”. The model represents five procedures: the first of them is market demand generated by the agent, called competitive environment; the second procedure is the construction of offer by competing agents; the third procedure are the rules of decision-making that define the agents’ behavior; the fourth procedure is the reward and its cost and benefit function; and finally, the procedure of unlearning, as a result of unlearning by not doing (UBND).

The competitive environment agent is the one demanding new goods and services with their respective attributes; this demand will be represented in a message called innovative opportunity. Similarly, the environment determines a random and localized demand in a period of time. The demand or innovative opportunity is defined by a vector l of n attributes, of a certain volatility (v) and lifecycle time (l_{ct}). If the system’s agents are capable of satisfying the demand, they will receive returns in said period. The supply is constructed through interaction between the competing agents and the competitive environment. A competing agent may respond and build one or many offers through its vector l of n capacities (for this model, $n = 5$); this construction may be individual or with other agents that may complement their capacities. The vectors for the two types of agents are made up by different positions and their respective magnitudes. Each position signals a specific attribute demanded by the environment and symbolizes in the competing agent the exploring and exploiting character of the agent’s capaci-

ties. Each capacity is defined in one of the five positions of the vector, as follows: the two positions at the right of the vector represent exploitative capacities (capacity for production and marketing); the two positions at the left represent capacities for exploration (capacity for R&D and resource management); and the central position represents capacities for intermediation. The magnitude of the positions in both vectors comprise initially random values between 0 and 9, representing the degree of the attribute require by the demand and the level of capacity of the competing agent (Fig. 1).

Interactions and rules of decision-making between agents are given through the two mechanisms mentioned in the theoretical framework. The first of them is the relational distance between agents and the second one is the distance of complementarity of capacities. Based on these two rules, offers by competing agents are built, as follows: once a competing agent interacts with the demand for the localization mechanism, the second interaction mechanism is initiated. This consists in comparing the magnitudes of both vectors (from right to left “RtL”); if the capacity vector is larger or equal in its last position to the demand’s attribute vector, demand will be visible for the competing agent and the comparative process will be repeated between the following positions (from right to left “RtL”) among the agents’ vectors. If a competing agent presents equal or comparatively larger magnitudes in relation to the demand’s attribute vector in all positions, then it will have set a success formula and it will be able to build an offer by itself.

Now, if the magnitude at the far right position of the capacity vector (marketing capacity) is less than the magnitude corresponding to the attribute vector, the agent will not identify the demand, as small as its geographic distance to the market demanding innovation may be; this behavior can be observed in market-pull innovation dynamics, as an innovation system exploiting agents are the ones with better capacity to visualize and evaluate a demand. In case the agent can identify the innovative opportunity but is not capable to configure a success formula by itself, it will look in its immediate geographic environment for other agents with whom to do it collaboratively; eventually, many collaborating agents may configure a success formula and leverage jointly the innovative opportunity.

Competing agents are born with resources conceived as the agent’s surplus stock (SS_t). This is assigned at random. The magnitudes of the attribute vector determine the maximum profit (B_t) that the competing agents may obtain for taking an innovative opportunity; these benefits represent the reward procedure. Agents that identify and appropriate a demand and satisfy an innovative opportunity through their offer will obtain returns that are calculated in each period of time (henceforward, tick). Returns are defined as the income or reward per attribute delivering the demand (IA). This income depends on the magnitude of each position of the demanded attribute and on the duration of the demand’s lifecycle (l_{ct}). The lifecycle of the demand for the model is random and a Gaussian behavior is assigned to it. It is worth keeping in mind that if the demand requests magnitudes or high levels from any attribute, the returns will be high. However, agents must also incur costs (C_t) in order to sustain the capacities with which they build success formulas. These costs are defined as the sum of magnitudes of the vector of the competing agent’s capacities in one tick; therefore, SS_t is calculated through Eq. (1).

$$SS_{t+1} = SS_t + B_t - C_t \quad (1)$$

The dynamics of unlearning are described in the model based on learning; this perspective is addressed from the resources and capacities of the competing agents. Taking into account the fact that learning is expressed in the vicinity of previous activities of the firms (Teecce, 1988), the model considers that agents that use their capacities will reinforce them thanks to experience and reward given by the environment, showing their learning by doing.

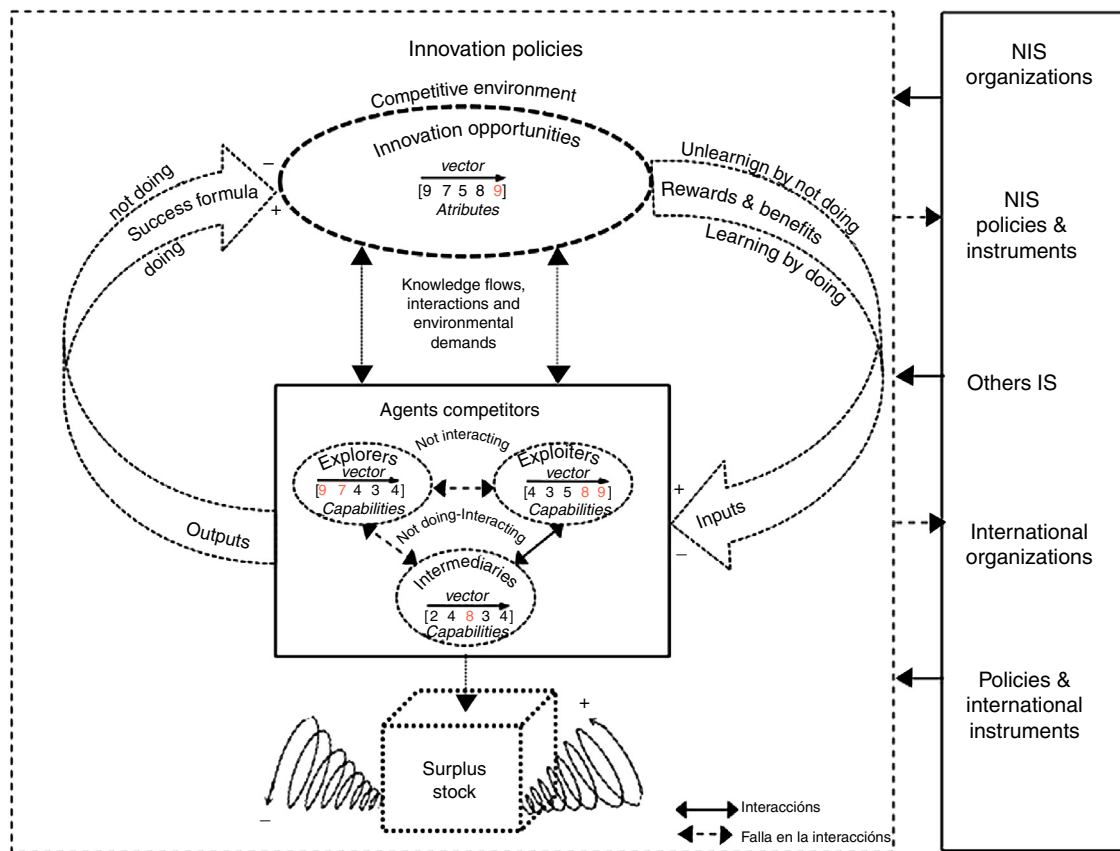


Fig. 1. Unlearning model in an innovation system.

Source: Prepared by the authors.

Likewise, the capacities that are not used will be debilitated, showing unlearning (UBND) until the agent loses them and dies. This behavior corresponds to an unlearning dynamic whose trajectories are sigmoid functions or S-shaped decreasing curves calculated through Eq. (2).

$$\frac{X}{1 + e^{\delta t}} \quad (2)$$

where X represents the magnitude or maximum value that a capacity may take, δ denotes the unlearning factor and t is the time in which the capacity is used. The less a capacity is used in time t , its deaccumulation resulting from not doing will present a trajectory depending on factor δ . For example, basic and advanced capacities (low and high magnitudes), when not used, show slower and more prolonged unlearning dynamics than intermediate capacities showing faster unlearning dynamics. The model emphasizes not only the interactive learning dynamics (Jensen, Johnson, Lorenz, & Lundvall, 2007; Lundvall, 2007), but also the unlearning dynamics, and in particular, the deaccumulation of innovative capacity due to lack of practice and use of some capacities or vector positions, which in some cases has a poor generation of competences in the system as a consequence.

4. Results and analysis

This phase consisted in building the computational model. To this end, the previous phases were translated into a flowchart (Fig. 2) and their corresponding source code into the Netlogo v. 5.1.0 platform. Also, the codification process was documented, specifying some significant details in the interface language. Finally, computational verification and validation of the model took place.

While the verification of the computational model cares for having the developed system executed as planned, validation cares for the model reflecting reality both in structure and behavior (Barlas, 1996). Specialized literature on ABMs and their empirical validation shows different approaches and techniques (Sargent, 2013; Windrum, Fagiolo, & Moneta, 2007).

At present, the model presented in this work has been verified and validated in its computational form. Validation of this behavior has been addressed from a validation technique called historical methods. This technique has three aspects: (1) historical methods from rationalism, (2) historical methods empirical, and (3) historical methods from positive economy, geared toward prospecting. The technique chosen for the validation of the model was the historical-rationalist method, which consists in verifying that the underlying suppositions from the model are true based on empirical studies presented by specialized literature.

Exploration of the behaviors in the studies conducted by Hobday (1995) in East Asian countries (South Korea, Taiwan, Hong Kong, and Singapore) indicate how the different firms from the electronics sector learned and accumulated technological capacities for innovation. These studies relate corporate learning patterns in conventional western models of innovation. Although the study is focused on electronics, it can be acknowledged that paths and patterns of technological learning vary from sector to sector. Said patterns were presented through interaction through subcontracting and manufacture. Interactions worked as a training school for the newly arrived enterprises, which made it possible to overcome entrance barriers for the assimilation in manufacturing and design of new technologies.

The newly arrived companies started having incremental improvement in their manufacturing processes, which led to

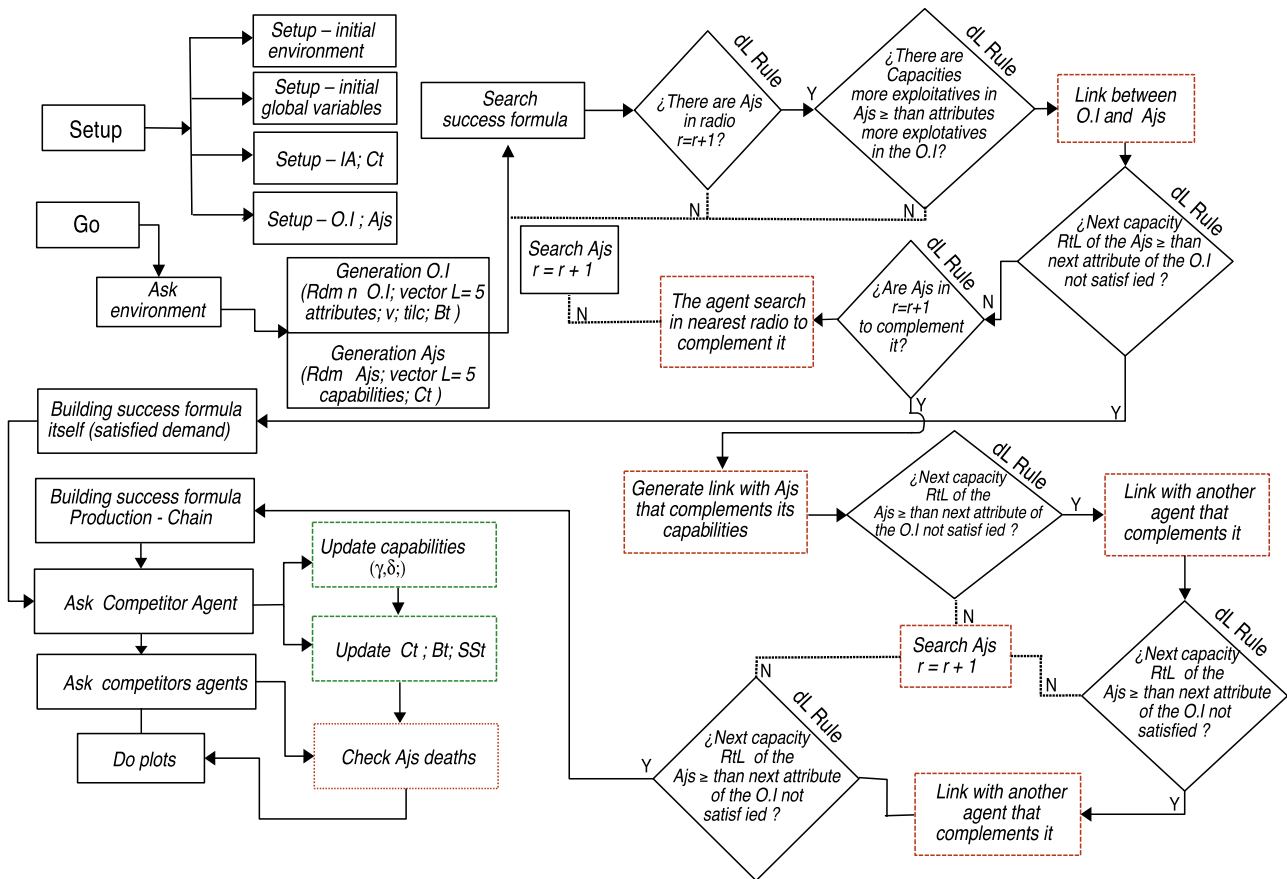


Fig. 2. Computational model flowchart.
Source: Prepared by the authors.

product innovations of lesser importance. It is worth mentioning that these improvements helped build and accumulate new production capacities by way of doing-interacting, and therefore, helped to unlearn other capacities that the environment was not demanding. Evidence suggests that the origins and paths of new arrivals are still influencing the strategies, structures, and technological orientations of the industries of the studied sector, propitiating the accumulation of technological capacities and learning, and also, propitiating technological deaccumulation or unlearning.

The model requires certain specific attributes like, for example, strict demands. These demands propitiate in some agents the impossibility of interacting (as a result of very low levels in their capacities), and therefore, the deaccumulation of capacities and unlearning. Dynamics of both learning and unlearning make it possible to find out how economic performance is generated in innovation system agents. Agents that are not capable of responding successfully to the demand through the construction of an offer, either autonomously or through interaction with other competing agents, will deaccumulate their capacities giving way to unlearning. It is worth highlighting that unlearning also enables agents to learn other capacities or positions as time goes by, which may facilitate interaction of the competing agent to participate in the demand propitiated by the competitive environment agent, as long as their assets or SS are enough for their survival. Table 2 presents the most significant variables of the calibrated model and their description.

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Agents that do not interact or participate with any of the five capacities for building demand will have little or no probability of learning and surviving in the system. This scenario is a result of the inability of agents to generate benefits and counter the cost of maintaining their capacities available. Innovation system showing prolonged unlearning dynamics without generating enough returns will reflect a precarious economic performance that will manifest in the decrease in surplus stock (SS) of competing agents and their later disablement. On the other hand, those who participate in one or more demands with their capacities will have a better probability of surviving in time. Figs. 3 and 4 represent the behavior of agents that survive, as well as the economic performance of the system in a 50-year period.

When competing agents adopt equal learning and unlearning factors, for example, $\delta = 0.3$, there is evidence of accumulation of capacities of the agents and a negative variation, which might be explained because some agents learn specific capacities while other unlearn said specific capacities, responding to the demand collectively through labor division, which leads to specialization. It is worth mentioning that these factors represent the accumulation or deaccumulation paths that the capacities of a competing agent may take within a given period. The accumulated SS of the competing agents supplying the demand reflects an economic performance

Table 2
Variable description.

Variables	Description
Vectors $l=5$	Chain length of a vector (attributes, capacities). Each position indicates the specific attribute of the demand and symbolizes the character of exploration, exploitation, or mediation of the competent agent.
Magnitudes	It represents the degree of the attribute in the demand and indicates the level of capacity in a competing agent; it comprises random values between 0 and 9.
Birth rate	Percentage of births of competing agents (6%) and demand of the environment (12%) in relation to the existing population in (t) . The goal of the rates is to represent a dynamic system. The range of density of new companies or enterprises that are born for the system to be kept alive in time are reported by the World Bank (Doing Business, 2013) in some Latin American economies.
Learning factor (δ)	The change in magnitude of one or more positions of the capacity vector adopted by competing agents in (t) . For the model, factors (δ) take values between 0.1 and 0.9.
l_{ct}	The period in which a successfully fulfilled demand produces returns. For the model, l_{ct} is random and has Gaussian behavior.
Reward income (IA)	The income or reward delivered by a demand in a position of its attribute. Agents capable of filling one or more positions with the capacity vector will receive this reward.
Cost (C_t)	The cost of sustaining a capacity in a position for a competing agent; this cost is directly proportional to the magnitude of the position of the capacity vector.
Surplus stock SS	The assets a competing agent has at the beginning of its creation or birth. All agents that participate in success formulas will have the possibility of increasing their SS as long as the returns are greater than their costs. This SS enables an agent to survive in time as long as the SS is positive. For the model, the surplus stock is random between 0 and 225 units.

Source: Prepared by the authors.

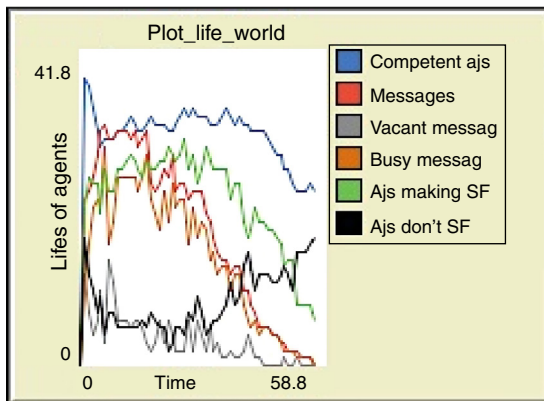


Fig. 3. Agents of the system.
Source: Plots Netlogo 5.1.0.

similar to all the competing agents in the system that are incapable of responding to the demand and which are therefore deaccumulating their capacities. That is to say, few competing agents respond to the demand; however, these few are generating enough benefits that reflect on the system's economic performance and its survival.

Negative variation in capacities may be interpreted as follows: competing agents who offer different demands use and utilize their capacities in one or many positions of their vector. However, each agent will deaccumulate or unlearn in the positions that it does not use or utilize for the construction of its offer. Therefore, negative variation denotes that few competing agents respond to the offer in one position, that is, as the offer is configured through interac-

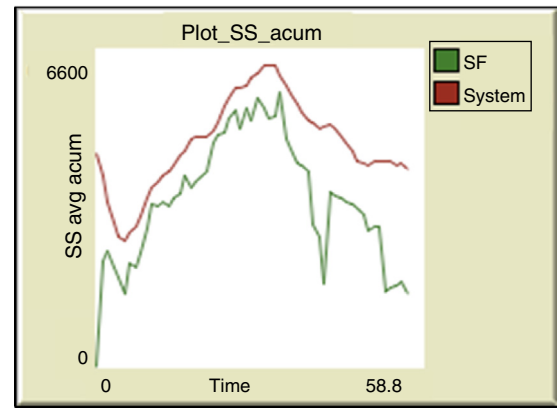


Fig. 4. Cumulative SS.
Source: Plots Netlogo 5.1.0.

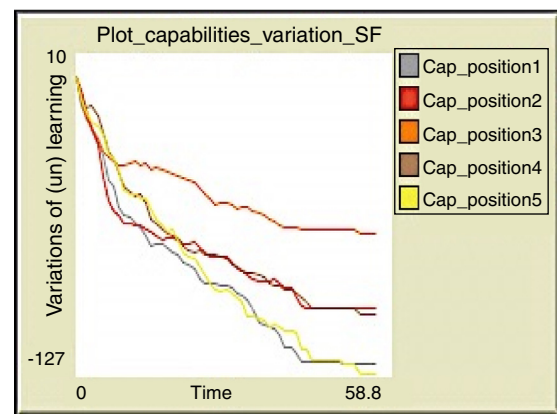


Fig. 5. Variation in capacities.
Source: Plots Netlogo 5.1.0.

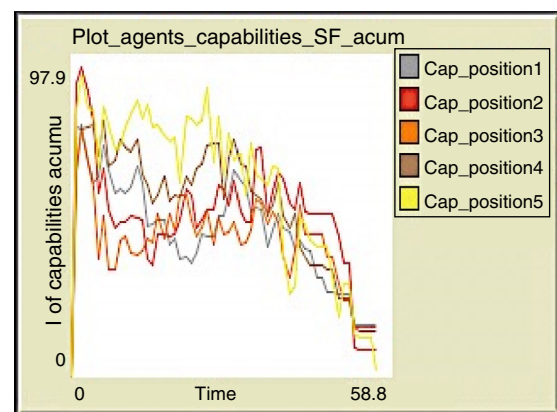


Fig. 6. Accumulation in capacities.
Source: Plots Netlogo 5.1.0.

tion between competing agents. These use one position at most to participate in the offer that fulfills the demand (Fig. 5). In other words, agents learn in some specific positions of their capacities, while in other positions they do not, thus configuring specialization and labor division. It is worth mentioning that agents with much higher capacities will take more time to lose them according to the unlearning factor assumed by the system. This indicates that past routines have been important for the agent, as Nelson and Winter (1982) suggest.

Fig. 6 shows how the system's agents accumulate capacities in certain positions; positive accumulation reflects learning by way of learning by doing and learning by interacting, reflecting thus the good economic performance in the system's cumulative SS.

5. Conclusions

Despite the fact that some innovation systems models address the concept of learning, little attention is paid to the process of unlearning as a new way of learning. Unlearning has been theoretically explored and developed extensively. However, when it comes to simulating innovative processes, available models make little emphasis on the process of unlearning.

The agent-based model proposed here aims at contributing to the understanding of the complex phenomena of innovation, learning, and unlearning in an RIS. Similarly, the model makes it possible to know the dynamics of unlearning and learning through interaction between agents and helps conduct and manage a region's policy, and in some cases, its strategy in order to improve the economic performance of the system's agents. The model has not been built to make forecasts; however, it enables the analysis of scenarios. The strength of the model lies in the possibility of integrating the theories, concepts, and relationships known in innovation processes from a bottom-up perspective, and under a single agent-based model.

The results of the work show the importance of unlearning in innovation systems, considering it as important as learning. Allowing them, through interaction with other complementary agents in their capacities and learning by doing. Agents can specialize and be more efficient in their actions by learning and unlearning. Knowing this is important for system agents and policy makers, since it is necessary to identify and act on the factors that encourage both learning (as has already been done) and unlearning.

As future work, the model can be replicated in RIS of high, medium, or low economic performance in order to observe their learning and unlearning dynamics. Also, the model can be improved in order to study the performance of an innovation system through the transaction costs of the agents mediating in the system. Finally, it is desirable to delve deeper into the learning and unlearning routines of the RIS, providing a better understanding of innovation systems' in aspects such as change and distribution of population characteristics in the system through interaction mechanisms such as selection, variation, and inheritance.

Conflict of interest

The authors declare no conflict of interest.

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