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Unlocking Coevolution and Inclusive Innovations: Dynamics of Marginalised Agents in Immature Innovation Systems

Maria Luisa Villalba , Danilo Spinola , Walter Ruiz

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Maria Luisa Villalba[*], Danilo Spinola[†], Walter Ruiz[‡]

Abstract

This article explores the coevolutionary dynamics of immature innovation systems (IMIS), focusing on the role of marginalized agents often excluded from Conventional Innovation Systems (CIS). Marginalized agents, such as informal entrepreneurs or low-resource communities, are key actors in addressing local challenges but are typically overlooked in mainstream innovation processes, making it crucial to understand how they can be integrated into broader systems. Using an Agent-Based Model (ABM) based on Villalba (2023) and Ruiz et al. (2016), we examine how interactions between agents with different innovation and inclusion capabilities drive system evolution. The model integrates learning and unlearning processes, allowing agents to adapt and build capabilities over time. Through simulations that vary social thresholds, agent configurations, NOPI (Needs, Opportunities, Problems and Ideas) complexity, and the presence or absence of learning, we find that while higher social thresholds and complex NOPIs foster agent specialization, they can limit the inclusion of marginalized agents. Conversely, the absence of learning results in system stagnation despite increased short-term inclusion. By adopting a system-wide perspective, this paper contributes to the literature on innovation systems by analyzing how the relationships between marginalized and conventional actors influence inclusion dynamics. Our ABM captures the complex interplay of inclusion, coevolution, and capability complementarity within IMIS, offering deeper insights into how marginalized agents drive inclusive innovation and emphasizing the importance of fostering both innovation and inclusion capabilities for sustainable, equitable outcomes.

Keywords: Coevolution, Heterogeneous agents, Immature innovation system, Developing countries, Excluded agents

JEL: O30; O35; L26

[*] Universidad Nacional de Colombia Sede Medellín, Facultad de Minas, Departamento de Ingeniería de la Organización. mlvillalbam@unal.edu.co
[†] Birmingham City University. danilo.spinola@bcu.ac.uk.
[‡] Universidad Nacional de Colombia Sede Medellín, Facultad de Minas, Departamento de Ingeniería de la Organización. wlruizca@unal.edu.co

1. Introduction

Innovation systems in developing countries often face challenges due to their immature and exclusive nature (Albuquerque, 2007; Villalba et al., 2023), characterized by weak institutional frameworks, limited access to resources, and a lack of cohesive policy support.[1] These systems are frequently dominated by conventional actors, such as established firms and research institutions, who focus primarily on economic gains through technological advancements. In contrast, marginalized groups, including informal entrepreneurs, smallholder farmers, and low-income communities, are often excluded from these processes despite their potential contributions to innovation.

The integration of excluded agents into innovation systems is crucial for achieving sustainable and inclusive economic growth (Urmetzer & Pyka, 2020). Inclusive innovation systems (IIS) seek to democratize the innovation process by involving a wider range of actors (Altenburg, 2009), particularly those traditionally excluded from conventional innovation systems (CIS). This approach aligns with global development agendas, such as the United Nations' Sustainable Development Goals (SDGs), which emphasize the need for inclusive and equitable economic growth.

A key mechanism supporting this integration resides in the concept of coevolution (Castellacci & Natera, 2013; Almudi & Fatas-Villafranca, 2021), as it captures the dynamic and interdependent nature of innovation processes involving diverse agents. Coevolutionary dynamics can foster adaptive learning, knowledge exchange, and the development of complementary capabilities, enabling marginalized agents to contribute to and benefit from the broader innovation system.

This study seeks to explore the coevolutionary dynamics of marginalized agents within an immature innovation system (IMIS).[2] An immature system, according to Albuquerque (1999), is characterized by underdeveloped science and technology infrastructure, weak interactions between research institutions and industries, and limited R&D investment from businesses. While some scientific infrastructure may exist, it is insufficient to drive technological innovation or industrial growth, making these systems reliant on external knowledge and technology and struggling to build self-sustaining innovation capabilities. We aim to understand how excluded agents, under certain conditions, can engage in productive collaborations with conventional actors and contribute to inclusive innovations in the context of an IMIS.

To address the challenges of exclusion and underdevelopment in immature innovation systems, it is essential to examine how marginalized agents can be integrated into these systems and contribute to inclusive innovation. This study aims to explore these dynamics by investigating the roles of government policies and conventional actors in fostering collaboration and innovation that meet the needs of marginalized communities.

The key research questions guiding this study focus on (1) the role of government and public policies in promoting opportunities for marginalized actors to enhance their innovation capabilities and collaborate with agents within conventional innovation systems (CIS), as well as (2) how these CIS agents can foster innovations that address local problems, particularly those affecting marginalized communities. To explore these questions, we propose an extension of the Agent-Based Model (ABM) developed by Villalba (2023), incorporating the dynamics of learning by doing, using, and interacting. This approach enables us to simulate various scenarios and evaluate the impact of different conditions on the emergence of inclusive innovation systems.

Although there is considerable research on *pro-poor* innovation (Bardegue, 2005; Kaplinsky, 2014; Abrol & Ramani, 2014) and on *bottom-of-the-pyramid* (Prahalad, 2012; Urmetzer& Pyka, 2020), few

[1] A typology of innovation systems has been explored in Albuquerque (2007).

[2] We use the acronym IIS to refer to Inclusive Innovation Systems and IMIS to refer to Immature Innovation Systems.

studies in the literature provide a comprehensive analysis of these dynamics within the broader context of innovation systems. In particular, the ways in which conventional systems can either create barriers or offer opportunities for the inclusion of marginalized agents. This paper proposes to contribute to filling this gap by adopting a system-wide perspective that examines the interactions between marginalized and conventional actors, considering how their relationships shape the inclusion process. Additionally, we contribute to the literature by employing an Agent-Based Model (ABM) to capture the complex dynamics of inclusion, coevolution, and capability complementarity within IMIS. This approach provides a deeper understanding of how marginalized agents in innovation systems can contribute to inclusive innovation, emphasizing the importance of fostering both innovation capabilities and capabilities for inclusion to achieve more sustainable and equitable outcomes.

After this introduction, we outline the structure of the paper as follows: in Section 2, we review the relevant literature on innovation systems, focusing on marginalized agents and their roles within these systems. In Section 3, we present the extended Agent-Based Model (ABM) used to simulate the coevolutionary dynamics between conventional and excluded agents in immature innovation systems. Section 4 describes the experimental setup and scenarios tested using the ABM, while Section 5 presents the results and key findings from the simulations. Finally, in Sections 6 and 7 we conclude with a discussion of the implications for policy and practice and suggest avenues for future research.

2. Literature Review

2.1 Innovation Systems and Marginalized Agents

The concept of innovation systems has undergone substantial development since its introduction (Freeman, 1987; Lundvall, 1992), now encompassing a range of contexts, including national, regional, and sectoral systems (Edquist, 2010). Much of the literature focuses on Conventional Innovation Systems (CIS), which are characterized by structured interactions among established firms, research institutions, and government bodies within an environment that reinforces innovation-driven solutions. In these systems, interactions, collaboration, and knowledge flows play a central role in generating new products and processes, diffusing them throughout the system, and creating benefits for all participating agents (Lundvall et al, 2009). However, the concepts of CIS, which offers a blueprint to constitute a virtuous system, and often overlook the contributions of marginalized agents (Berdegue, 2005; Urmetzer & Pyka, 2020), whose informal and necessity-driven innovations do not fit neatly within conventional frameworks.

Marginalized agents, such as informal entrepreneurs and smallholder farmers, are those that often engage in innovative activities out of necessity, driven by the need to address immediate local challenges (Urmetzer and Pyka, 2020). Very prominent in developing countries, these agents typically operate outside formal networks and institutional support, relying on indigenous knowledge, frugal innovation practices, and community-based solutions (Sen & Kliksberg, 2007). While their innovations may lack the formal recognition and scale of conventional innovations, they are crucial for addressing pressing local issues and enhancing community resilience (Prahalad, 2012).

The framework for Inclusive Innovation Systems (IIS) (Altenburg, 2009; Chataway et al., 2014; Villalba, 2023) builds upon the structures of conventional systems but emphasizes inclusivity and the integration of marginalized agents. The theoretical basis for this shift stems from the recognition that innovation can and should be a tool for social inclusion, addressing issues of inequality and exclusion (Arocena & Sutz, 2021). In inclusive systems, the interactions among agents—both established and marginalized—are key to fostering innovation that benefits not only the market but also socially excluded groups.

Villalba et al. (2023) explores the IIS framework by examining how these systems emerge and evolve through the participation of excluded agents. Inclusive innovation systems require a broader understanding of the diverse capabilities of agents, particularly those who may not have traditionally participated in the innovation process. The complementarity of innovation capabilities and capabilities for inclusion becomes crucial, as these systems rely on the interactions between agents with different but complementary capabilities to co-create solutions that address both economic and social challenges.

2.2 Coevolution in Innovation Systems and Agent-Based Modeling

A key aspect of this dynamic is the concept of coevolution, which plays a vital role in the development of innovation systems. Coevolution refers to the process through which two or more entities, such as species, organizations, or agents, evolve in response to each other's actions and adaptations (Gowdy, 1994; Almudi & Fatas-Villafranca, 2021). In the context of innovation systems, coevolution highlights the interdependent development of agents, their capabilities, and the institutional environment. It emphasizes the importance of reciprocal interactions, mutual learning, and adaptive responses in shaping the evolution of innovation ecosystems (Nelson & Winter, 1982; Kallis, 2007).

The concept of coevolution is particularly relevant for IIS (Villalba et al., 2023). In these systems, marginalized agents and conventional actors coevolve, influencing each other's strategies, behaviors, and outcomes (Guha-Khasnobis et al, 2006). For instance, socially conscious firms may develop new business models that integrate the capabilities of marginalized agents, while the latter may enhance their skills and knowledge through these interactions.

To capture this coevolutionary mechanisms, Agent-Based Modeling (ABM) has been used as a powerful tool for exploring the dynamics of complex systems, such as innovation systems. It allows for the simulation of interactions among heterogeneous agents, each with distinct characteristics, decision-making processes, and adaptive behaviors. This approach is well-suited to studying the emergent properties of systems where individual actions and interactions lead to system-level outcomes (Gilbert et al., 2001a; Epstein & Axtell, 1996). In innovation studies, ABM has been used to examine knowledge diffusion, network dynamics, and the impact of policy interventions, simulating scenarios that include diverse agents, varying interaction mechanisms, and evolving capabilities.[3] These models provide insights into how different agents—firms, universities, NGOs, and marginalized actors—interact, learn from one another, and co-create innovations that address social and economic needs.

Contributions on the use of ABM for IIS include Villalba (2023), which simulate how marginalized agents can drive innovation within IIS, particularly in contexts characterized by resource constraints, such as frugal innovation. The SKIN model[4], initially developed by Gilbert et al. (2001b), has been refined, expanded, and modified in subsequent works, including Ahrweiler et al. (2004), Gilbert et al. (2007), Pyka et al. (2007), Pyka and Scholz (2008), Pyka et al. (2009), Ahrweiler et al. (2011), and Triulzi et al. (2011). Additionally, the hypercycles model[5], introduced by Padgett (1997) and later extended by Padgett et al. (2003, 2009) and Watts and Binder (2012), offers further insights into these dynamics.

[3] The use of ABMs provides insight into the mechanisms through which the behaviour and interactions of micro-agents—such as firms, universities, government entities, NGOs, and marginalized actors—contribute to the development of an innovation system.

[4] The **SKIN** (Simulating Knowledge Dynamics in Innovation Networks) model is an ABM designed to study knowledge creation, sharing, and innovation within networks of firms. It simulates the coevolution of knowledge and network structures through learning processes like learning-by-doing and learning-by-interacting, emphasizing the heterogeneity of firms and their collaborations (Gilbert et al., 2001b).

[5] The hypercycles model study the cooperative dynamics of self-replicating entities. Agents represent different types of replicators that support each other's replication through catalytic interactions, forming interconnected cycles (hypercycles).

The SSRIS model[6], conceptually grounded in the organizational learning system proposed by Schwandt and Marquardt (2000), extracts four building blocks to form the subsystems of the conceptual models by Zollo et al. (2011), Iandoli et al. (2013), and Ponsiglione et al. (2014). Lastly, the innovation system model, which highlights the complementary nature of capabilities and learning to exploit innovation opportunities, was first developed by Ruiz et al. (2016) and later expanded by Quintero et al. (2017, 2019).

The strength of ABMs lies in their ability to model non-linear interactions and emergent phenomena, making them ideal for studying complex adaptive systems like inclusive innovation systems (Kiesling et al., 2012). By simulating different scenarios, ABMs can reveal leverage points and critical factors that influence the success of innovation initiatives within these systems. This makes them a valuable tool for policymakers and researchers seeking to design interventions that promote inclusivity and innovation.

3. Model Extension and Formulation

In this section, we present an enhanced Agent-Based Model (ABM) based on Villalba (2023), incorporating new dynamics to better capture the learning processes and coevolutionary interactions of marginalized agents within immature innovation systems. The model includes three key learning processes: (1) **Learning by Doing**, where agents enhance their capabilities through hands-on experience and iterative problem-solving, reflecting necessity-driven innovation; (2) **Learning by Using**, which involves agents adapting existing technologies to local contexts; and (3) **Learning by Interacting**, where agents engage with both excluded and conventional actors, fostering knowledge exchange, capability development, and system-wide coevolution.

Agents are characterized by vectors of innovation capabilities and capabilities for inclusion. Innovation capabilities relate to R&D, diffusion, linkage, production, and market exploitation, while capabilities for inclusion involve social connectivity, agency, teaching-learning spaces management (TLSM) capabilities, and integrating traditional knowledge in production and commercialization of new appropriate solutions. The model accounts for agent heterogeneity: marginalized agents generally possess lower formal innovation capabilities, while conventional agents excel in innovation but often lack social connectivity. Interaction mechanisms, including knowledge exchange, collaboration formation, and adaptation, drive coevolution, enabling agents to influence one another's development through shared learning. The ABM formalizes these interactions using equations that capture agents' evolving states, offering insights into the mechanisms driving inclusive innovation.

The model consists of two different types of agents: the first is called Competitive Environment, where NOPI (Needs, Opportunities, Problems and Ideas) are generated[7], which are composed of attributes that must be met by the competing agents who want to satisfy, take advantage of and/or solve them. The second type of agents is grouped together with the competing agents, who have capabilities that are made available to projects that seek to account for the NOPI. These agents are of various kinds: some are in charge of exploring and generating new knowledge (research centers, laboratories, universities, etc.); there are also interface entities, which have the purpose of connecting different kinds of competing agents so that knowledge flows between them (Technological development centers, innovation intermediaries, technological brokers, etc.); others are in charge of exploiting it (firms); and there are the excluded agents, who do not possess any of these capabilities recognized in the CIS, but who possess

[6] **SSRIS** (Social Simulations for Research on Inclusive Systems) explores the dynamics of inclusive innovation systems. It simulates how diverse agents, including marginalized groups, interact within innovation ecosystems, examining how learning, collaboration, and policy interventions impact innovation processes and social inclusion.

[7]

other fundamental capabilities to fulfill new functions that allow addressing the social component of the NOPI as discussed in depth in the work of Villalba et al (2023).

What is sought is that in the model these agents interact as follows: First, the agents seek to take advantage of the NOPI by fulfilling their attributes, which are found in the Inclusive Environment. They do this either individually or through interaction with other agents, using and complementing their capabilities if necessary. It should be clarified that the rules of interaction between the agents depend on the geographic location, first, and then on the complementarity of their capabilities. Second, by managing to take advantage of a NOPI, the competing agents learn by increasing those capabilities that were used and unlearn by decreasing those capabilities that were not; in this way the agents co-evolve, thanks to the interaction with the NOPI of the Inclusive Environment and with the other agents with whom they interact. Third, agents that manage to take advantage of NOPI are rewarded by the Inclusive Environment, thus increasing their energy (using a biological metaphor) to be able to survive in the system. Together, these agent types form a dynamic and interactive network, where each plays a role in the coevolution and development of the innovation system.

Each agent type in the model is defined by distinct attributes that shape its behavior and interactions. The capabilities of agents are categorized into two types: $capInoTra$, which represents conventional (traditional) innovation capabilities, and is expressed as a vector $[c_1, c_2, \dots, c_n]$, where each element denotes a specific skill or competency relevant to conventional innovation processes. The second type, $capIncl$, captures capabilities for inclusion, defined by the vector $[c_1', c_2', \dots, c_m']$, which reflects the agent's potential to engage in inclusive innovation, emphasizing social connectivity, trust-building, and collaboration with marginalized actors. These capabilities define the agent's ability to contribute to both conventional and inclusive innovation efforts.

In addition to capabilities, competing agents possess economic attributes that influence their financial decision-making and resource management. The cost attribute represents the expenditure required to maintain or develop an agent's capabilities, while the benefit attribute reflects the gains obtained from successful engagements or transactions. Additionally, the SExe attribute refers to the stock of surpluses, which are the net resources available after deducting costs from the agent's benefits. Lastly, agents have interaction attributes, particularly $nopiLink$, which indicates connections to market opportunities, or NOPIs. These links are established when the agent's capabilities align with the specific requirements of a NOPI, facilitating collaboration and the pursuit of innovation opportunities.

Agents interact with NOPIs (Needs, Opportunities, Problems, and Ideas) through a capability matching mechanism that evaluates the compatibility between an agent's capabilities and the requirements of a NOPI. The capability matching function assesses potential links by comparing the agent's conventional ($capInoTra$) and inclusive ($capIncl$) capabilities against the innovation and inclusion attributes of the NOPI. A match is determined if the agent's capabilities meet or exceed the NOPI's requirements. Mathematically, the matching function is defined as:

$$Match(A, N) = \prod_{j=1}^{n} \mathrm{I}\left(capInoTra_{A,j} \geq attrInoTra_{N,j}\right) \times \prod_{k=1}^{m} \mathrm{I}\left(capIncl_{A,k} \geq attrIncl_{N,k}\right) \quad (1)$$

where I is an indicator function that returns 1 if the agent's capability matches or exceeds the corresponding requirement of the NOPI, and 0 otherwise. This function ensures that only agents with adequate conventional and capabilities for inclusion are eligible to engage with specific NOPIs.

Once a match is identified through the capability matching process, the agent proceeds to link formation, governed by specific decision rules. If an agent's capabilities sufficiently align with a NOPI's requirements, a link is established, enabling interaction and collaboration between the agent and the NOPI. If no match is found, the agent continues searching for alternative NOPIs that better fit its capabilities. These decision rules ensure that agents only form productive links where they can contribute meaningfully, driving innovation and inclusion within the system through targeted collaborations.

Learning and unlearning

The learning and unlearning dynamics in the model allow agents to continuously adapt their capabilities, reflecting real-world processes of skill acquisition and loss. Learning is modelled as an increase in an agent's capabilities through increments associated with where on the "S"-shaped technological learning curve the capability is currently at when used, which are scaled by a learning rate. This is expressed mathematically as:

$$capInoTra_i' = capInoTra_i + \Delta learn, \tag{2}$$

$$capIncl_i' = capIncl_i + \Delta learn \tag{3}$$

where $\Delta Learn$ is an increment given by the learning factor given to the context in which the agents interact, and which is affected by the moment of the "S" curve in which the capability is located. Through this process, agents improve both their conventional and inclusive capabilities, enhancing their potential to engage in innovation activities and form links with relevant NOPIs. Conversely, unlearning captures the process by which an agent's capabilities decrease, either due to skill decay or a shift in focus to other competencies. This process is modelled similarly to learning, but with a negative increment:

$$capInoTra_i' = capInoTra_i - \Delta Unlearn \tag{4}$$

$$capIncl_i{}' = capIncl_i - \Delta Unlearn \tag{5}$$

where $\Delta Unlearn$ represents the loss of capabilities over time. Unlearning is a critical aspect of the system, as it reflects the dynamic nature of agent capabilities, where skills not actively used may degrade. The balance between learning and unlearning, updated at each time step, affects the agent's ability to form links with NOPIs and successfully participate in innovation transactions, ensuring a constantly evolving system where agents must adapt to remain competitive and effective.

The economic performance of agents in the model is driven by three key factors: cost, surplus, and profit calculations. Cost calculation is based on the agent's capabilities, with the total cost determined by the sum of capability values multiplied by corresponding system-specific cost coefficients. Mathematically, this is represented as:

$$Cost_i = \sum_{j=1}^{n} c_j \cdot CC\_System_j \tag{6}$$

where c_j represents the agent's capabilities and CC_System_j refers to the associated cost coefficients for each capability. This function ensures that agents with higher levels of capabilities incur greater costs to maintain or develop those capabilities.

Surplus is updated by balancing the agent's costs and the benefits obtained from successful transactions. The surplus calculation is expressed as:

$$SExe_i = SExe_i - Cost_i + Benefit_i \tag{7}$$

Here, benefits are derived from the level of capability matching with linked NOPIs, with better matches yielding higher benefits. In addition to managing their surplus, agents also calculate their expected profit by considering both transaction costs and current surpluses. Expected profit is modeled as:

$$Expected\_Profit_i = \alpha \cdot (Cost_i + Transaction\_Costs_i) \tag{8}$$

where α is a scaling factor that reflects the agent's potential profitability based on the cost of their transactions and their engagement with NOPIs. This dynamic process allows agents to continuously adapt their strategies based on economic performance, influencing their future decisions and interactions.

Initialization

The model's initialization begins by assigning random capabilities to both agents and NOPIs within predefined limits, ensuring heterogeneity among the entities and the coherence with the reality. This initialization sets the stage for the system's evolution over discrete time steps. Each time step represents a moment where agents adjust their capabilities, attempt to form links with NOPIs, and engage in economic activities. These interactions are driven by the agents' current attributes, including their innovation capabilities and capabilities for inclusion. The evolving interactions and learning processes allow agents to continuously refine their strategies and capabilities as they seek out profitable opportunities in the system.

Additionally, the simulation introduces mechanisms for agent creation and termination. New agents and NOPIs are introduced into the system according to predefined birth rates, ensuring a dynamic flow of entities entering the system. Conversely, underperforming agents may exit if they fail to meet specific performance thresholds, such as maintaining sufficient surplus or forming successful links with NOPIs. Throughout the simulation, agents regularly reassess their capabilities, balancing between learning new skills and unlearning obsolete ones. This dynamic adjustment ensures agents can adapt to the system's evolving conditions, making the environment highly responsive and fostering continuous innovation and interaction among agents.

The dynamics of agents in the model are governed by key equations that dictate how their capabilities and economic status evolve over time. For capability updates, agents adjust both their conventional and inclusive capabilities at each time step. The equations governing these changes are:

$$capInoTra_{i,t+1} = capInoTra_{i,t} + \eta(Learning\_Rate) - \gamma(Unlearning\_Rate) \tag{9}$$

$$capIncl_{i,t+1} = capIncli, t + \eta'(Learning\_Rate) - \gamma'(Unlearning\_Rate) \tag{10}$$

where η and γ represent stochastic terms that determine the rates of learning and unlearning, respectively. This ensures that agents can both gain new skills through learning and lose them over time through unlearning. The balance between these two processes enables agents to dynamically adjust their capabilities based on interactions and environmental conditions within the system.

Economic updates are similarly driven by the agents' capability adjustments and transaction outcomes. The cost an agent incurs at each time step is calculated based on their conventional capabilities and system-specific cost coefficients:

$$Cost_{i,t} = \sum_{j=1}^{n} capInoTra_{i,j,t} \cdot CC_{System_j} \tag{11}$$

$$SExe_{i,t+1} = SExe_{i,t} - Cost_{i,t} + Profit_{i,t} \quad (12)$$

reflecting the dynamic balance between costs incurred, benefits gained, and the agent's overall economic performance. Finally, agents decide to form links with NOPIs based on a matching condition:

$$Link\_Decision = \begin{cases} 1, if\ Match(A, N) = 1 \\ 0, otherwise \end{cases} \quad (13)$$

If a match is successful, the agent forms a link, facilitating collaboration and economic transactions. This decision rule ensures that agents only engage in interactions that are aligned with their capabilities, driving meaningful connections within the innovation system. Each variable used in the model is explained in detail in Annex 1.

The Agent-Based Model (ABM) outlined above seeks to understand the dynamics of IMIS and IIS by simulating interactions between agents and the NOPI framework. The model includes mechanisms for agents to adjust their capabilities through both learning and unlearning processes, enabling adaptation and improvement in economic performance over time. By adjusting key parameters, such as learning rates and cost coefficients, the model simulates different scenarios to examine the impact of various strategies for promoting innovation and inclusion.

4. Experiment

The experimental design explores the effects of varying specific parameters on the dynamics of our ABM. To configure the scenarios, we varied four key parameters: 1) social level, 2) initial configuration of agents, 3) initial configuration of NOPIs based on their complexity, and 4) the presence or absence of learning processes. Each parameter was varied independently while holding other parameters constant, such as the birth rate of NOPIs, the birth rate of agents, transaction costs, maintenance costs of capabilities, the number of initial agents, learning-unlearning factors, income per attribute, and surplus stock. This section details the setup of each experimental scenario.

For each case, we conduct Monte Carlo experiments using 20 different random seeds, running the model for 200 time steps. The calibration is based on reasonable assumptions, designed to represent quarterly periods. Annex 2 provides the initial values for each scenario.

Experiment 1. Social Level

In Experiment 1, we explore the role of the social level in influencing the inclusion of marginalized agents. The social level is a parameter that ranges from 1 to 9, with a value of 4 defined in the original model as the threshold for a NOPI (Needs, Opportunities, Problems, and Ideas) to be considered social. To understand how varying this parameter affects the inclusion of agents, the experiment tests social levels of 2, 4, 6, and 8, while keeping other model parameters constant. This variation allows for the assessment of how changes in the social level impact the classification of NOPIs as social and, consequently, the inclusion of marginalized agents in the innovation process.

The different scenarios tested show distinct impacts on inclusion. At a social level of 2, the lower inclusion threshold reduces the number of NOPIs classified as social, which may limit the participation of agents with agency and TLSM capabilities. The baseline scenario with a social level of 4 reflects the baseline original model's assumptions. At a social level of 6, a higher inclusion threshold potentially allows more agents with agency and TLSM capabilities to engage excluded agents in innovation activities. Finally, a social level of 8 approaches the maximum threshold, testing the limits of inclusion by enabling a broad spectrum of agents with higher agency and TLSM capabilities interact with NOPIs and they promote marginalized agents to participate in innovation dynamics. This experiment provides insights into how the social level parameter can be adjusted to enhance or restrict inclusion in the innovation system.

Experiment 2. Changes in the Initial Configuration of Agents

In Experiment 2, we explore the impact of the initial configuration of agents on the early dynamics of the innovation system by altering the baseline scenario from Villalba (2023). The baseline starts with a balanced distribution of agents, reflecting a mix of both innovation capabilities and capabilities for inclusion. For this experiment, two alternative conditions were tested. In the Formal Agents Only condition, all agents possess conventional innovation capabilities but lack inclusive innovation skills. This setup simulates a formal market environment where innovation is driven primarily by agents with conventional, market-focused capabilities. In contrast, the Informal Agents Only condition introduces agents who lack conventional innovation capabilities but possess low-level inclusive innovation capabilities, representing a system dominated by informal agents more focused on inclusive innovation processes.

In both scenarios, the total number of agents and their birth rates were kept constant, ensuring that any differences in the system's dynamics were attributed to the change in agent type configuration. The Formal Configuration scenario examined how the system operates when only innovation-focused agents are present, assessing how exclusion from inclusive processes impacts overall innovation. Conversely, the Informal Configuration scenario evaluated the dynamics when only inclusion-focused agents were active, exploring the potential of informal agents to drive innovation without conventional capabilities. This experiment provides insights into how the composition of agents influences the development and outcomes of the innovation system, particularly in terms of balancing formal and informal contributions.

Experiment 3. Initial Configuration of NOPIs

In Experiment 3, the initial configuration of NOPIs (Needs, Opportunities, Problems, and Ideas) is examined to understand how their complexity influences agent engagement and innovation dynamics within the system. NOPIs are characterized by specific attributes that define the capabilities agents must possess to interact with them, with attribute values ranging from 0 to 9, where 9 represents the highest capability required. Two scenarios were developed for this experiment. The Non-Complex NOPIs scenario sets all attributes to 1, creating a system with low complexity. This configuration tests how easily accessible opportunities, with minimal capability requirements, affect agent behavior and the overall dynamics of the innovation system.

In contrast, the Complex NOPIs scenario assigns the maximum value of 9 to all NOPI attributes, establishing a system with high complexity. In this scenario, only agents with the highest capabilities are capable of engaging with these NOPIs, testing the system's capability to handle demanding opportunities. The Non-Complex Configuration allows for widespread agent participation due to minimal barriers to entry, while the Complex Configuration assesses the system's behavior when only highly capable agents can participate, exploring the potential for specialization or exclusion. This experiment sheds light on how varying levels of NOPI complexity impact agent interactions, opportunity access, and the overall performance of the innovation system.

Experiment 4. Absence of Learning

In Experiment 4, the model tests the impact of eliminating learning and unlearning processes to understand their importance in the innovation system's dynamics. One of the core assumptions of the original model is that agents and NOPIs continuously evolve through learning, which allows for the enhancement of both innovation and inclusive capabilities. In this experiment, all learning factors were set to zero, effectively halting any capability development or adaptation. This included learning factors related to NOPIs, agents' innovation capabilities, agents' inclusive capabilities, and the processes involved in teaching and knowledge transfer. By removing these elements, the experiment creates a baseline scenario in which agents cannot improve their skills or adapt to new opportunities.

The No Learning scenario allows for an exploration of how static capabilities affect the interactions and outcomes within the system. Without the ability to learn or unlearn, agents are unable to adjust to evolving demands or improve their match with NOPIs over time, leading to stagnation in innovation activities. This experiment provides a valuable contrast to scenarios where learning is present, helping to highlight the critical role that continuous capability development plays in fostering dynamic interactions, adaptability, and overall system growth. The results offer insights into how learning mechanisms are essential for sustaining innovation and inclusion in evolving environments.

In all experiments, several parameters were held constant to ensure that any variations in outcomes were directly attributable to the primary variables being investigated. One of these controlled parameters was the birth rate of NOPIs, which was set at 3% with an exponential growth pattern. This rate was chosen because a 2% rate was found to result in zero net growth, while the 3% rate ensured a steady but manageable increase in NOPIs, preventing an overwhelming influx of opportunities in the system. Similarly, the birth rate of agents was held proportional across agent types, with significant effects only observed at rates above 18%. This allowed for the controlled emergence of agents within the system, with the assumption that 45% of agents are excluded to reflect realistic population dynamics.

Other controlled factors included transaction costs and capability maintenance costs, which were fixed across all scenarios to maintain a consistent economic environment for agents. Additionally, the initial number of agents was kept the same in every experiment, ensuring that population size did not influence the outcomes, allowing the focus to remain on the changes in agent configurations or NOPI complexity. The factors of learning and unlearning were also consistent across all experiments, except in the scenario testing the absence of learning, where they were set to zero. This control structure ensured that the observed effects in each experiment could be reliably attributed to the specific variables being tested, providing a clear understanding of their influence on the innovation system's dynamics.

5. Results

Based on the results presented in the Table 1, we can analyze several key variables related to marginalized agents, inclusion, and the overall system dynamics across various experiments. The experiments provide insight into how different social levels, complexity of NOPIs, and the presence or absence of learning influence the inclusion of marginalized agents and the performance of the innovation system. **The results for Experiment 2 will not be reported, as all agents disappear in this scenario, demonstrating that a system entirely dominated by marginalized agents is unable to sustain itself.** We opted to remove the graphs from Experiment 2 from our graphs.

One of the primary variables to assess the inclusion of marginalized agents is **agentsInSuccessFormulasExcluded**, which tracks the number of excluded agents that are part of successful innovation processes. In the baseline scenario (Exp 1 - Social Level 4), the number of excluded agents involved in successful formulas is 2.68. This number increases as the social level rises to 6 and 8, reaching 2.93 and 7.12, respectively. This suggests that higher social levels contribute to greater inclusion of marginalized agents in successful innovation activities. However, in Exp 3 (Complex NOPIs), this number drops to 1.74, indicating that the complexity of opportunities can hinder the participation of excluded agents, likely due to the high capability requirements. Conversely, in Exp 3 (Non-Complex NOPIs), the number of excluded agents participating in success formulas remains similar at 1.63, indicating that lower complexity does not significantly improve their inclusion. In Exp 4 (No Learning), the number of excluded agents in successful formulas spikes to 9.10, a surprising result that might suggest that the lack of capability evolution allows excluded agents to capitalize on static opportunities, though this does not necessarily translate to long-term system health. These results can be observed in Graph 1.

The **totalExcludedAgents** variable provides further insight into how many agents remain marginalized across the different scenarios (see Graph 2). In the baseline, 4.65 agents are excluded, but this number increases significantly as the social level rises, with 11.41 excluded agents at the social level 8. This implies that despite higher social levels potentially offering more opportunities for success, a larger portion of the agent population remains marginalized. The results for the complex and non-complex NOPI scenarios show fewer excluded agents (3.99 and 3.88, respectively), suggesting that in these scenarios, a higher percentage of the agent population is able to engage with opportunities. However, in the No Learning experiment, the number of excluded agents rises sharply to 22.01, which indicates that the absence of learning significantly increases marginalization. A deeper look at the behavior over time of the variable **totalExcludedAgents** reveals that the social level scenarios 2 and 4, the complex and non-complex NOPI scenarios, and the No Learning scenario show a reduced growth in the number of excluded agents over time, while in the social level scenario 8 this variable shows an increasing behavior (see Graph 3). This implies that this extreme configuration generates positive effects by facilitating the involvement of excluded agents in the use of NOPIs, but at the same time it may not generate sufficient benefits for excluded agents to change their excluded status.

The **agentsInSuccessFormulasNotExcluded** variable indicates the number of non-excluded agents that are successfully engaging in innovation processes. In the baseline, 32.37 non-excluded agents are involved in successful formulas. As social levels increase, this number fluctuates, reaching 31.23 at social level 6 and dropping to 28.29 at social level 8. This suggests that higher social levels do not necessarily guarantee greater success for non-excluded agents. Interestingly, both the complex and non-complex NOPI scenarios see higher participation of non-excluded agents (50.73 and 55.70, respectively), indicating that opportunity complexity plays a critical role in determining the overall success rates of agents. In the No Learning scenario, the number drops to 47.98, which suggests that the absence of learning slightly reduces the success of non-excluded agents, though they still perform better than in the baseline.

The sustainability variables, such as **social**, **economic**, and **ecological** provide insight into the overall sustainability of the system in each scenario. In the baseline, social sustainability is relatively low at 2.61, while economic sustainability is also low at 1.29, and ecological sustainability is at 2.12. These values improve as social levels rise, with significant increases seen at social levels 6 and 8. In Exp 3 (Complex NOPIs), these values spike dramatically, particularly for economic (5.08) and ecological (4.48) sustainability, suggesting that more complex opportunities lead to more sustainable outcomes for the system overall. However, in the No Learning scenario, ecological sustainability drops to 4.61, while social sustainability remains relatively low at 5.82, indicating that without learning, the system struggles to maintain long-term sustainability despite short-term gains in certain areas. This analysis is illustrated in Graph 4 including combinations of different directionality according to the three sustainability dimensions: equitable, viable, supportable, economic, social, and ecological.

In addition to the above, two distinct patterns emerge over time. In scenarios where only the level of inclusion is modified, the variables show little variation over time. However, in scenarios where changes are made to the complexity of NOPIs, the configuration of agents, or learning values, the level of variation is significantly higher (see Graph 5). These results highlight the substantial impact that different configurations can have on immature innovation systems, particularly in terms of system stability and adaptability.

The **inclusiveWithLinks** and **conventionalWithLinks** variables track the number of NOPIs (inclusive and conventional) that agents successfully engage with. The behavior over time of this variable is similar in all scenarios (see Graph 6), thus it is important to perform its analysis based on the average values identified in Table 1. In the baseline, 9.66 inclusive NOPIs have links, while 15.35 conventional NOPIs have links. As the social level increases, the number of inclusive NOPIs with links rises to 11.13 at social level 6 and 13.40 at social level 8. This suggests that higher social levels provide more inclusive opportunities for agents to engage with. On the other hand, the number of conventional NOPIs with links remains relatively stable, with a significant rise in Exp 3 (Non-Complex NOPIs), where 27.06 conventional NOPIs have links, indicating that lower complexity leads to more conventional opportunities being exploited. In Exp 4 (No Learning), inclusive NOPIs with links remain similar (11.41), but the number of conventional NOPIs with links rises significantly to 25.17, suggesting that without learning, agents can still capitalize on static conventional opportunities.

Several variables track the specialization of agents, such as **hybridExploiter**, **conventionalIntermediary**, and **scientificExplorer**. In the baseline, hybrid exploiters and conventional intermediaries have moderate engagement, with values of 7.65 and 2.31, respectively. As social levels rise, the number of hybrid exploiters decreases, particularly at social level 8, where it drops to 4.77. Similarly, conventional intermediaries increase in Exp 3 (Complex NOPIs) to 6.49, suggesting that higher complexity fosters greater specialization. The scientific explorer role sees a notable increase in Exp 3 (Complex NOPIs), reaching 8.66, which suggests that more complex environments encourage scientific exploration. In Exp 4 (No Learning), the scientific explorer role is significantly diminished, dropping to 4.68, indicating that learning is crucial for fostering specialized roles like scientific exploration.

Finally, the **highCost** and **mediumHigh** variables provide insight into the economic performance of agents in each scenario. In the baseline, the high cost is 1277.98, and medium-high cost is 636.02. These costs rise as the social level increases, with a particularly sharp increase at social level 8, where high cost reaches 1609.52. In Exp 3 (Complex NOPIs), these costs rise even further to 1364.45, suggesting that complex environments require higher investments from agents. In contrast, in Exp 3 (Non-Complex NOPIs), costs are relatively lower, indicating that simpler environments are less economically demanding. In Exp 4 (No Learning), costs are significantly reduced, particularly for high-cost agents (999.60), which indicates that the absence of learning reduces the financial burden on agents, though this may come at the cost of long-term system performance.

6. Discussion

The results from this study offer important insights into coevolutionary theory, particularly in the context of immature innovation systems involving marginalized and conventional agents. The data from the experiments reveal how marginalized agents, although often limited in formal innovation capabilities, can still contribute significantly to the system's coevolutionary dynamics through their higher inclusion-related skills. These findings emphasize the importance of capability complementarity. In scenarios where the social level was higher (Experiment 1, Social Level 8), marginalized agents were more integrated into the system, illustrating that even agents with lower formal innovation capabilities can drive necessity-driven innovations when social conditions are conducive. This suggests that marginalized agents are not only recipients of innovation but active contributors to system change, challenging conventional perspectives that prioritize only formal innovation capabilities. Emphasizing the importance of the role of agents with agency and TLSM capabilities, since this type of agent is the one who gives visibility to the excluded and helps them to improve their skills so that they can be integrated into the dynamics of innovation.

Furthermore, the dynamic interaction between agents demonstrates the crucial role of learning and unlearning processes. The absence of learning in Experiment 4 illustrates the negative consequences of stagnation. Without these adaptive processes, the inclusion of marginalized agents is severely limited, and the overall system becomes less capable of evolving to meet changing demands. This reinforces the idea that learning, both formal and informal, is essential to the ongoing development and resilience of innovation systems, particularly those in their immature stages. The data thus support the coevolutionary view that both marginalized and conventional agents must continuously adapt through mutual interactions to foster innovation.

For policymakers, the findings show that enabling the inclusion of marginalized agents requires more than simply encouraging innovation; it necessitates policies that enhance both innovation capabilities and capabilities for inclusion. In scenarios where social thresholds were set higher, marginalized agents became more involved in the success formulas, suggesting that fostering inclusion is directly linked to more socially supportive environments. Practical interventions could involve creating platforms for knowledge exchange between conventional and marginalized agents, especially in sectors like agriculture or frugal technology, where informal innovation has a larger role to play. Moreover, public policy needs to invest in both educational programs and the social infrastructure that builds trust between agents, enabling marginalized groups to interact more effectively with conventional agents. That may be through the promotion of the existence of agents with agency and teaching-learning spaces management capabilities. Experiments where social level was elevated (Experiment 1, Social Level 8) demonstrated a marked increase in successful collaborations, which suggests that promoting social cohesion within innovation ecosystems is a critical lever for coevolutionary development.

For conventional actors such as firms and research institutions, the results underscore the importance of actively engaging marginalized agents. Recognizing their unique contributions can lead to partnerships that are not only innovative but also more resilient in the face of social and economic challenges. This study shows that conventional agents benefit from such engagement by diversifying the capabilities present in the system, thereby driving system-wide learning and adaptation.

While the Agent-Based Model (ABM) provides meaningful insights into the dynamics of inclusion within innovation systems, there are certain limitations that require attention. The experiments focused heavily on the impact of social levels and learning mechanisms but did not explore the full complexity of agents' decision-making processes. Introducing more nuanced decision-making algorithms, which account for economic constraints, risk preferences, and policy impacts, could offer deeper insights into how different types of interventions shape coevolutionary dynamics. Future research should also investigate how varying institutional, cultural, and regulatory environments influence the role of marginalized agents in immature innovation systems. Expanding the model in these ways will provide a more comprehensive understanding of how to nurture inclusive innovation in a variety of contexts.

7. Conclusion

This study provides critical insights into the coevolutionary dynamics of marginalized agents within immature innovation systems, particularly in the context of developing countries. By employing an Agent-Based Model inspired by Villalba (2023), we demonstrate that marginalized agents—despite often having lower formal innovation capabilities—play a vital role in fostering inclusive innovation. The model reveals that the complementarity of capabilities between conventional and marginalized agents drives system-wide coevolution, emphasizing the importance of learning, unlearning, and adaptive interactions.

Our findings emphasize the significance of capability complementarity in advancing innovation, revealing that higher social thresholds allow greater participation of marginalized agents in innovation processes. However, the study also underscores the essential role of capability development: when learning processes are absent, the system stagnates, restricting long-term sustainability. Notably, when the system is dominated by marginalized agents with limited learning potential, stagnation leads to systemic collapse.

This research advances the understanding of how marginalized agents contribute to the evolution of innovation systems by stressing the importance of continuous learning and adaptive coevolution. The study illustrates the need for environments that encourage collaboration and capability building, enabling innovation systems to become more inclusive, resilient, and capable of addressing both local and broader societal challenges.

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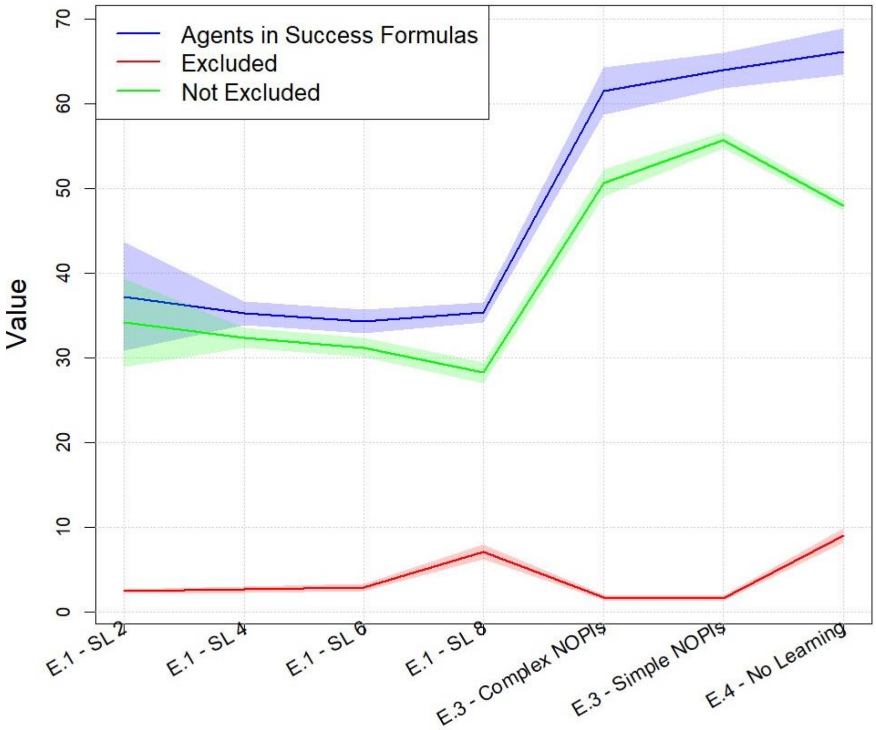
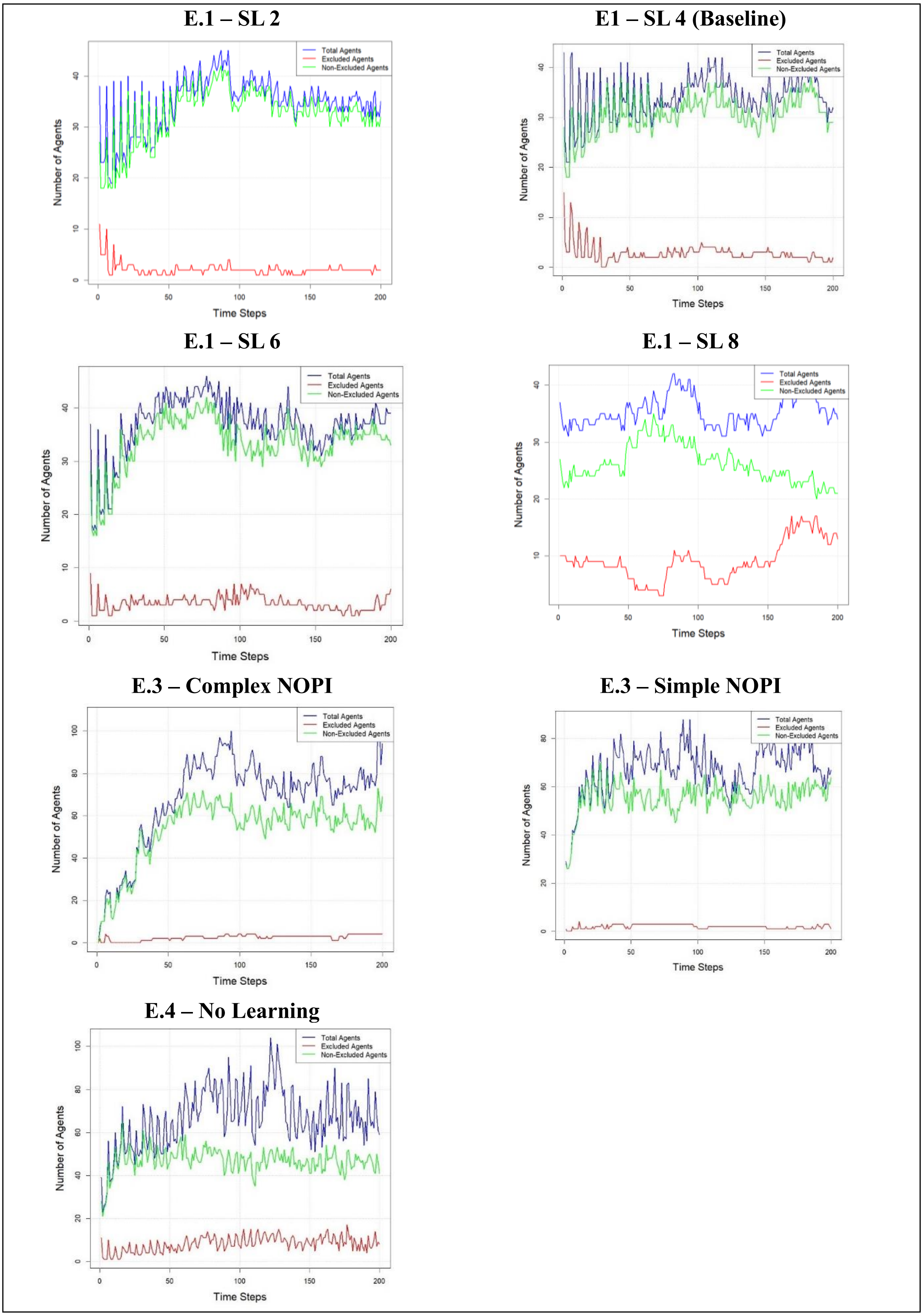
Graph 1. Average of Number of agents in success formulas per experiment. (20 simulations, 200 Time Steps)[8]



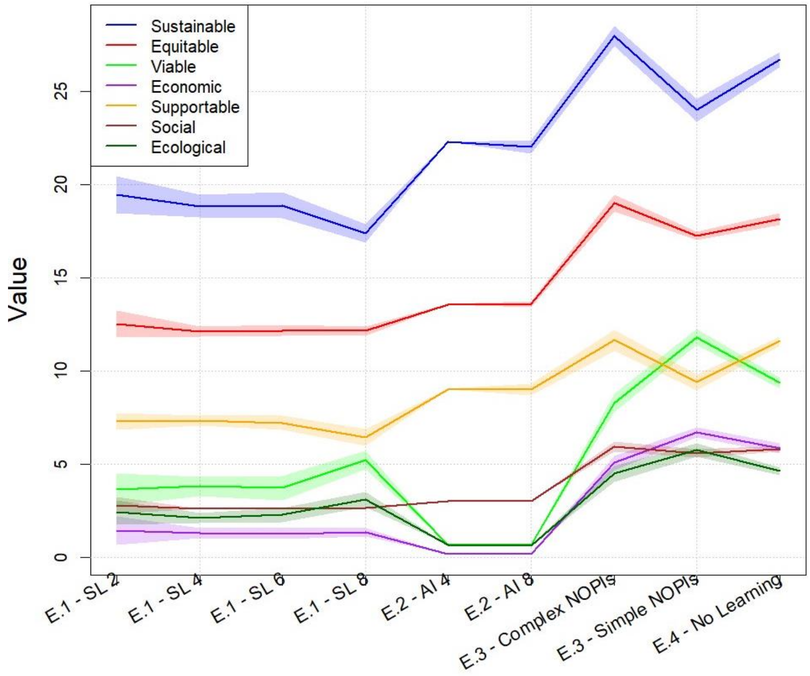
Graph 2. Average Total Agents and Excluded/Non-Excluded Agents per Experiment (20 Simulations, Time Steps)

[8] Experiment 2 showed zero agents, so we opted to remove from those graphs.

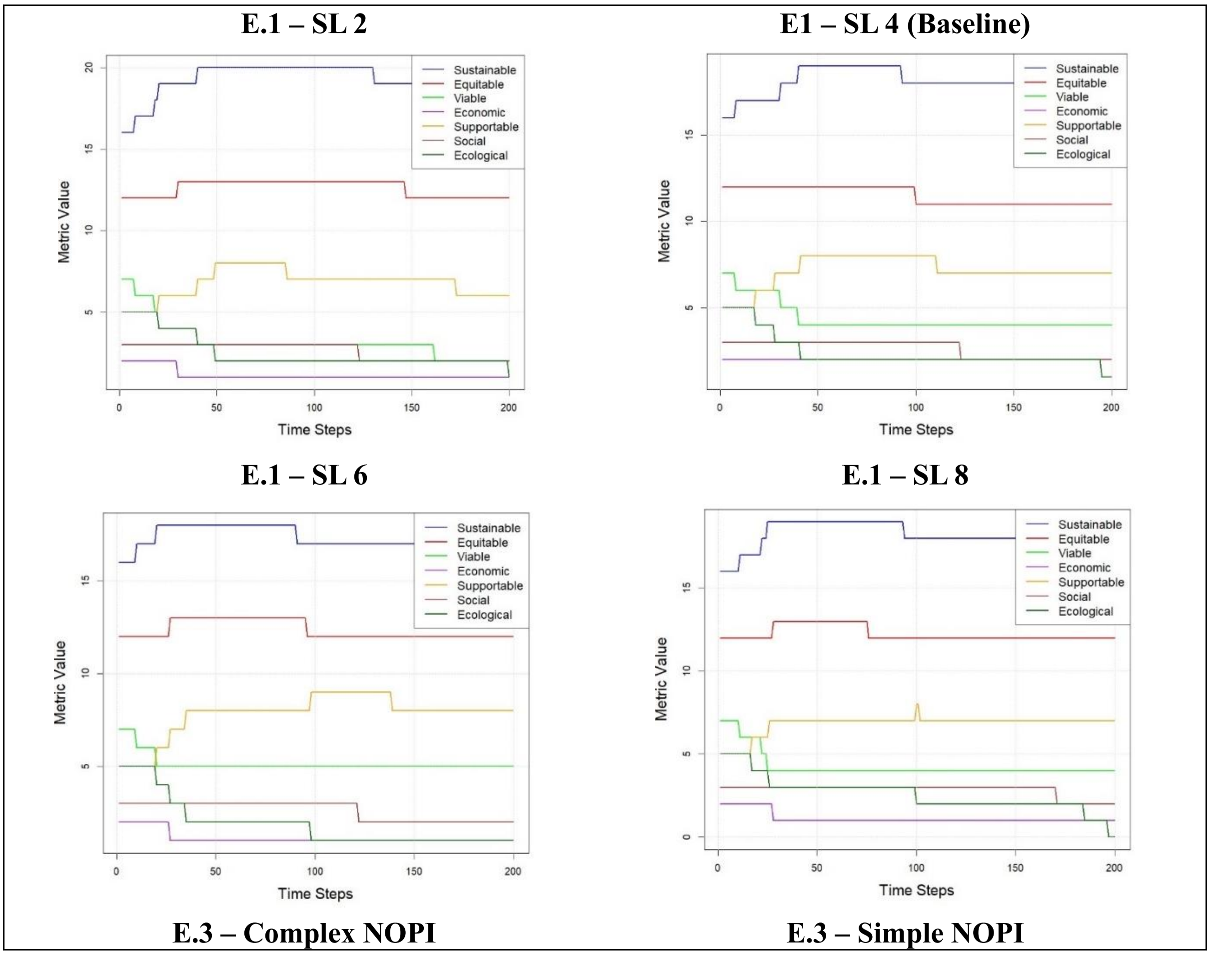
Graph 3. Agent Count Over 200 Time Steps – Single Simulation

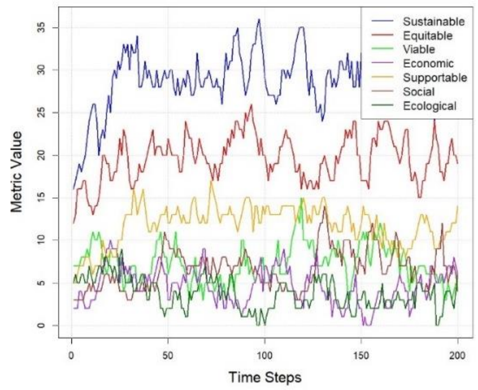


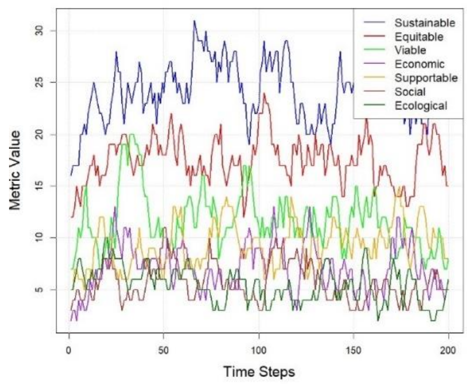
Graph 4. Average Sustainability Metrics per Experiment (20 Simulations, 200 Time Steps)



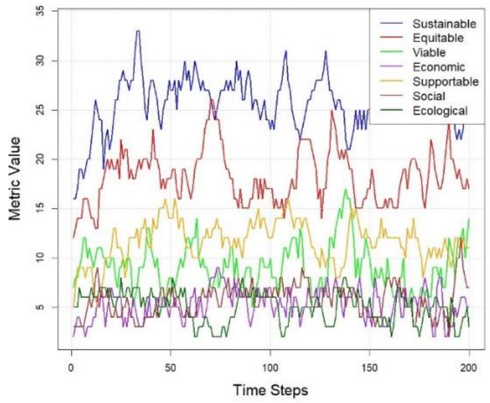
Graph 5. Sustainability Metrics Over Time – Single Simulation Across 200 Time Steps





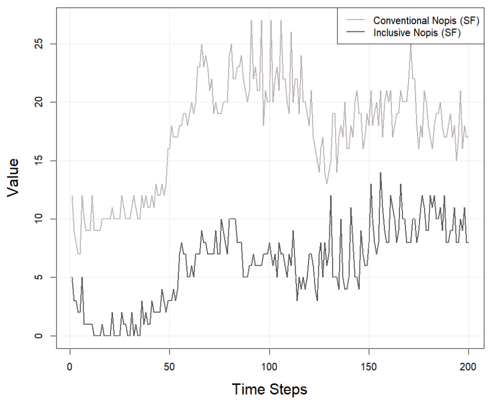


E.4 – No Learning

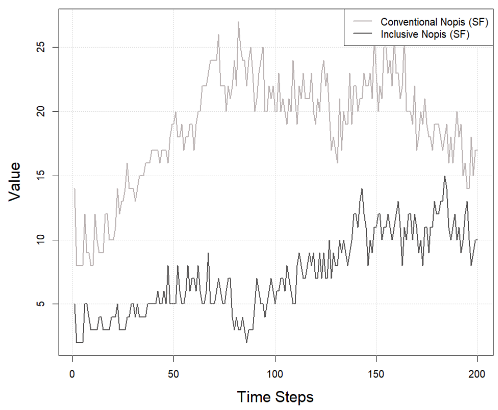


Graph 6. Number of Utilized NOPIs – Results from a Single Simulation Over 200 Time Steps

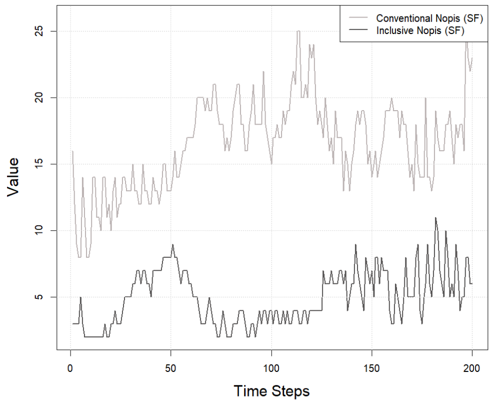
E.1 – SL 2



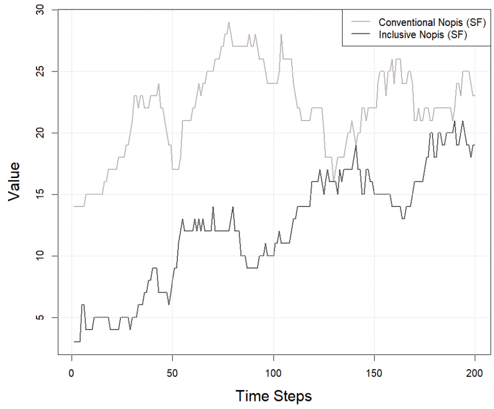
E1 – SL 4



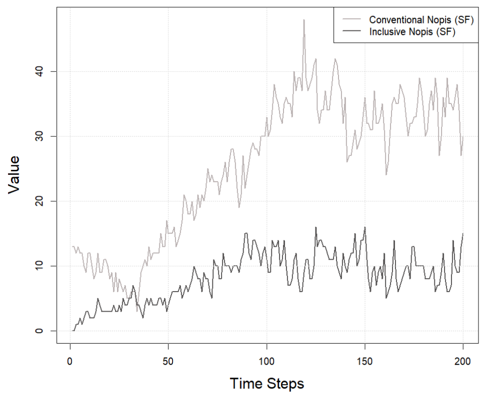
E.1 – SL 6



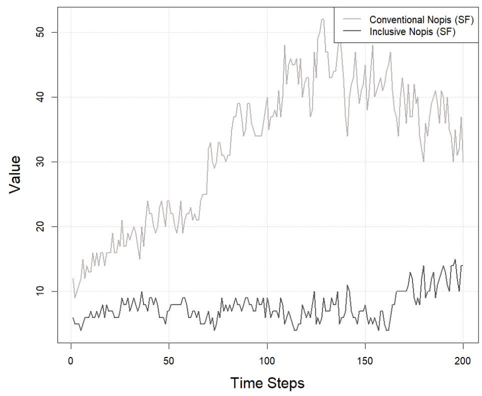
E.1 – SL 8



E.3 – Complex NOPI



E.3 – Simple NOPI



E.4 – No Learning

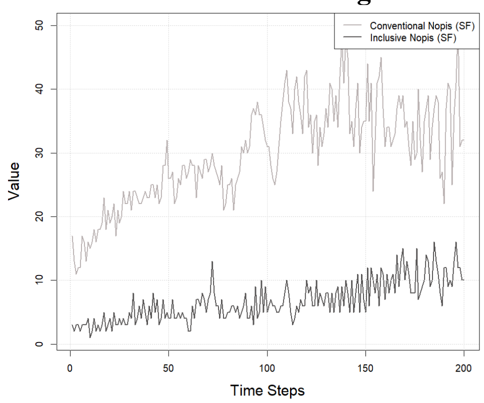


Table 1. Average Results of Monte Carlo Simulations (200 Time Steps, 20 seeds)

Variable	E 1 S=2	E1 S= 4 (BL)	E1 S=6	E1 S=8	E3 – Complex Nopis	E3 – Less Comples Nopis	E4 – Zero Learning
totalAgents	49.64	48.12	48.15	48.30	84.76	82.78	84.39
agentsInSuccessFormulas	37.29	35.31	34.35	35.41	61.58	64.02	66.21
agentsInSuccessFormulasExcluded	2.47	2.68	2.94	7.12	1.74	1.63	9.10
totalExcludedAgents	4.25	4.65	5.38	11.42	3.99	3.88	22.01
totalNonExcludedAgents	45.39	43.47	42.77	36.88	80.76	78.90	62.39
totalAgentsCEA	13.88	13.57	12.17	0.00	22.84	22.21	37.67
ceaExcluded	0.96	1.22	1.53	0.00	0.57	0.59	13.81
sustainable	19.46	18.85	18.90	17.40	27.97	24.00	26.72
equitable	12.53	12.13	12.18	12.14	19.02	17.25	18.15
viable	3.63	3.80	3.71	5.22	8.30	11.81	9.35
economic	1.44	1.29	1.27	1.35	5.08	6.70	5.83
supportable	7.29	7.33	7.21	6.45	11.66	9.39	11.60
social	2.78	2.61	2.61	2.64	5.93	5.59	5.82
ecological	2.41	2.12	2.27	3.09	4.48	5.77	4.61
equitableNoLink	6.20	6.04	6.56	7.96	7.64	8.96	7.48
viableNoLink	3.17	3.43	3.35	4.95	4.27	8.68	6.79
economicNoLink	1.24	1.16	1.14	1.24	2.00	4.14	3.88
supportableNoLink	3.30	3.34	3.45	3.82	4.40	4.42	4.96
socialNoLink	1.18	0.94	0.93	1.35	1.84	2.47	2.82
ecologicalNoLink	1.91	1.63	1.81	2.71	2.03	4.14	2.99
agents	49.64	48.12	48.15	48.30	84.76	82.78	84.39
inclusive	20.99	13.30	6.48	0.00	14.50	13.46	16.26
excluded	4.25	4.65	5.38	11.42	3.99	3.88	22.01

Annex 1. Variable Definitions and Corresponding Code References

The code is available upon request from the authors

Names for the paper	Names from the code	Explanation
time steps	Ticks	Number of time steps or iterations in the simulation
totalAgents	Total agentes	Total number of agents in the system
totalNonExcludedAgents	Total Agentes no excluidos	Total number of non-excluded agents
totalExcludedAgents	Total Agentes excluidos	Number of excluded agents
agentsInSuccessFormulas	Agentes en formulas de éxito (SF)	Number of agents in successful formulas
agentsInSuccessFormulasExcluded	Agentes en formulas de éxito excluidos (SF Exclu)	Number of excluded agents in successful formulas
agentsInSuccessFormulasNotExcluded	Agentes en formulas de éxito no excluidos (SF No Exclu)	Agents not excluded in successful formulas
totalAgentsCEA	Total Agentes CEA	Total number of agents with teaching learning capability (CEA)
ceaExcluded	CEA excluidos	Number of excluded agents in teaching learning processes
ceaNotExcluded	CEA no excluidos	Number of not-excluded agents in teaching learning processes
sustainable	sostenible	Number of agents with sustainable directionality
equitable	equitativo	Number of agents with equitable directionality
viable	viable	Number of agents with viable directionality
economic	economico	Number of agents with economic directionality
supportable	soportable	Number of agents with supportable directionality
social	social	Number of agents with social directionality
ecological	ecologico	Number of agents with Ecological directionality
undefined	indefinido	Number of agents with undefined directionality
nopis	Nopis	Needs, opportunities, problems and ideas in the system that require targeted capabilities from agents to be addressed
conventionalNopis	Nopis convencionales	Number of conventional NOPIs in the system
inclusiveNopis	Nopis inclusivas	Number of Inclusive NOPIs in the system
conventionalWithLinks	Convencionales con enlaces	Number of conventional NOPIs addressed by agents
inclusiveWithLinks	Inclusivas con enlaces	Number of inclusive NOPIs addressed by agents
hybridExploiter	explotadorhibrido	Hybrid agents (conventional and excluded) who exploit knowledge
conventionalIntermediary	intermediarioconvencional	Conventional intermediaries
conventionalExploiter	explotadorconvencional	Conventional exploiters of scientific knowledge
excludedExploiter	explotadorexcluido	Excluded exploiters of traditional knowledge
hybridExplorer	exploradorhibrido	Hybrid agents (scientific and excluded) who explorer knowledge
scientificExplorer	exploradorcientifico	Conventional explorers of scientific knowledge
inclusiveIntermediary	intermediarioinclusivo	Inclusive intermediaries
excludedExplorer	exploradorexcluido	Excluded explorers of traditional knowledge
allExcluded	todosexcluido	Excluded agents who have all of capabilities for inclusion

Names for the paper	Names from the code	Explanation
circle	circle	Excluded agents who have a low level in all of their capabilities for inclusion
allConventional	todosconvencional	Conventional agents who have all innovation capabilities
highCost	Costo_ alto	High transaction cost between agents
mediumHigh	medio_alto	Medium-high transaction cost between agents
medium	medio	Medium transaction cost between agents
mediumLow	medio_bajo	Medium-low transaction cost between agents
low	bajo	Low transaction cost between agents
averageCapabilitiesSF	Promedio Capacidades SF	Average capabilities in success formulas
averageCapabilities	Promedio Capacidades	Average overall capabilities of all of agents
averageInclusiveCapabilitiesSF	Promedio Capacidades SF Inclusivas	Average of capabilities for inclusion in success formulas
averageConventionalCapabilitiesSF	Promedio Capacidades SF Convencionales	Average of innovation capabilities in success formulas
sexeSF	Sexe SF	Surplus stock of agents in success formula
sexeSystem	Sexe System	Surplus stock of agents in the overall system
accumulatedSexeSF	Acum Sexe SF	Accumulated surplus stock of agents in success formula
accumulatedSexeSystem	Acum Sexe System	Accumulated surplus stock of agents in the overall system
costsSF	Costos SF	Costs of agents in success formulas
costsSystem	Costos System	Costs of agents in the overall system
accumulatedCostsSF	Acum Costos SF	Accumulated costs of agents in success formula
accumulatedCostsSystem	Acum Costos System	Accumulated costs of agents in the overall system
benefitsSF	Beneficios SF	Benefits from Nopis in success formulas
benefitsSystem	Beneficios System	Benefits from Nopis in the overall system
accumulatedBenefitsSF	Acum Beneficios SF	Accumulated benefits from Nopis in success formulas
accumulatedBenefitsSystem	Acum Benficios System	Accumulated benefits from Nopis in the overall system
accumulatedCapabilitiesSF	Acum Capacidades SF	Accumulated capabilities in success formulas
variationsCapabilitiesSF	Variaciones Capadidades SF	Variations in capabilities in success formulas
variationsCapabilities	Variaciones Capadidades	Variations in capabilities in overall system
ceaLinksCounter	Contador Links CEA	Counter of teaching learning process links
end	FIN	End of the simulation or system analysis

Annex 2. Initial Values by Scenario

(Only the modified values for each experiment are reported in the experiment columns)

Parameter	**Initial value**	E 1 S=2	E1 S=4 (BL)	E1 S=6	E1 S=8	E2 S=4	E2 S=8	E3 – Complex Nopis	E3 – Less Complex Nopis	E4 – Zero Learning
Inclusion level (S)	4	2	4	6	8		8			
Initial number of nopis	50									
Initial number of agents	50									
Percentage of excluded agents	45%					100%	100%			
Percentage of complex Nopis	50%							100%	10%	
NOPI birth rate	3%									
Agents birth rate	20%									
Learning factor by use of capabilities	3%									0%
Unlearning factor by use of capabilities	2%									
Learning factor by teaching learning processes	0,13 %									
learning processes time (ticks)	4									
Maximum surplus stock	6000									
Maximum life cycle time of innovations	120									
Maximum volatility of NOPI	60									
Benefits from NOPIs by conventional attribute	40									
Benefits from NOPIs by inclusive attribute	20									
Maintenance costs of innovation capabilities	4									
Maintenance costs of capabilities for inclusion	1									
High transaction cost between agents	1.0									
Medium-high transaction cost between agents	0,7									
Medium transaction cost between agents	0,5									
Medium-low transaction cost between agents	0,3									
Low transaction cost between agents	0,1									

* Experiment 2 modifies the initial agent distribution.

Annex 3. Summary of Experiments and Key Insights

Experiment	**Focus**	**Scenarios**	**Insights/Outcomes**
Experiment 1: Social Level	Impact of social level on inclusion of marginalized agents	Social levels: 2, 4 (baseline), 6, 8	- Higher social levels (6, 8) increase the inclusion of marginalized agents in innovation. - Social level 8 shows more agents with agency/TLSM capabilities interacting with NOPIs. - Extreme inclusion at social level 8 risks higher exclusion of other agents.
Experiment 2: Changes in Initial Agent Configuration	Impact of agent composition on system dynamics	Formal Agents Only vs. Informal Agents Only	- Formal Agents Only scenario limits inclusion; driven by conventional market-focused innovation. - Informal Agents Only boosts inclusion but lacks formal innovation capabilities. - System dynamics change significantly depending on the initial agent composition.
Experiment 3: Initial NOPI Configuration	NOPI complexity and its effect on agent engagement	Non-Complex NOPIs vs. Complex NOPIs	- Non-Complex NOPIs allow for broader agent participation due to low barriers. - Complex NOPIs demand high capabilities, fostering specialization but limiting access to marginalized agents.
Experiment 4: Absence of Learning	Effect of eliminating learning/unlearning on system dynamics	No Learning scenario (learning factors set to zero)	- No Learning leads to static system dynamics. - Despite higher short-term inclusion of marginalized agents, long-term innovation stagnates. - Learning is essential for system adaptability and sustained growth.