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Wind of change for agent decisions and innovation diffusion: The ASPID predictive model for technology adoption

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ABSTRACT

Innovations are part of human evolution and are essential for survival. However, traditional innovation diffusion models do not contemplate the possibility of innovation failure and focus on imitation social processes that require historical data for their estimation, providing only ex-post information, which limits their usefulness for risk management operations. This paper proposes a more general new model (ASPID: AbS-based Predictive Innovation Diffusion model) focusing on the decisions of agents who exhibit intentional limited rationality (IBR). ASPID provides: i) a greater depth of ex-post analysis than the classical models; ii) ex-ante information on the innovation diffusion process based on the characteristics of the target agents, the quality of the innovation, and the network topology of their relationships; iii) the success probability since innovations can fail. The model's versatility allows it to adapt to any information level, from the most aggregated to the most detailed. Some ex-ante and ex-post examples are presented to support the contribution.

1. Introduction

Innovation management is a key element in the success of organizations and countries. Public intervention in innovations is justified by the externalities and asymmetric information problems that generate significant divergences between social and private returns [1], which depending on the sector and type of innovation, reaches ratios of 2:1 to 4:1 [2]. Innovations exhibit three types of externalities [3]: (1) knowledge-generated externalities that benefit third parties without compensation to the innovator; (2) network externalities, where the value of technology increases with the number of users; and (3) adoption externalities, where early adopters assume costs and risks that benefit later adopters. These externalities are particularly intense in disruptive technologies aimed at sustainability [4] and, due to the limited vision of private actors, can cause potentially valuable innovations to fail despite offering benefits superior to existing alternatives [5], with failure rates of 60 % at the initial phases of diffusion [6,7]. Acemoglu et al. [8] estimate that these failures represent losses equivalent to 1–2 % of global GDP annually in avoidable environmental costs.

However, the effectiveness of public intervention requires predictive capacity in the models used for policy design and evaluation. Traditional models, such as Bass [9] and Fisher-Pry [10], have limitations that compromise their predictive utility, underestimate the complexity of adoption dynamics and overestimate the probabilities of success [11]. Especially important is the inability of these models to predict innovation failures, both errors of omission (rejection of superior technologies) and errors of commission (adoption of suboptimal technologies), which limits their applicability in public planning [12–15]. Literature reviews converge on three critical deficiencies.

1) Absence of theoretical frameworks that integrate individual idiosyncratic elements with systemic perspectives [12,16–19];
2) Lack of incorporation of individual decision-making processes that reflect bounded rationality [17,20–22];
3) Lack of models that capture sophisticated network effects and contemporary communication and distribution systems [12,14,16,17].

To address these deficiencies, we develop an Agent-based Predictive Innovation Diffusion (ASPID) model that structures diffusion processes as a result of a set of decision problems with mutual influences, surpassing previous approaches focused exclusively on social imitation [21]. Our analysis relaxes the assumptions of perfect rationality, implementing the concept of intentional bounded rationality (IBR),

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where agents recognize their fallibility and use social information as additional signals in decision-making processes [23,24]. Methodologically, we employ an agent-based approach (ABM) to analyze emergent dynamics in complex systems with autonomous decision-making entities. The model formalizes independent variables (latent performances of alternatives, cognitive capacity of the decision-maker, and structure of social systems) and dependent variables (speed and probability of success in diffusion processes). The proposed probabilistic framework assumes that the performance of innovations is uncertain and difficult to anticipate, where decision uncertainty depends on individuals' capacities and mutual influences of agents in social networks [25]. This approach makes it possible to establish predictions about the evolution of successful and unsuccessful innovations, based on the causal mechanisms of individual agents' decisions.

The main research contributions of this work are.

1) The formalization of a decision model that incorporates essential cognitive elements such as stimuli, value generation, and potentials cognitive biases.
2) The implementation of IBR to incorporate errors into decisions.
3) The simultaneous integration of individual effects and a global perspective, demonstrating that classical models constitute specific cases of our framework.
4) The enabling of complex interactions across networks that simulate diverse relational contexts.

The central methodological implications are the predictive capacity of innovation failure, distinguishing between errors of omission and commission, and the ex-ante prediction capacity of diffusion evolution, considering structural elements of the model such as network architecture, product characteristics, and cognitive parameters.

Therefore, the ASPID model responds to needs identified by organizations such as the International Energy Agency [26] by providing predictive tools that incorporate agent heterogeneity, network effects, and probability of technological failure, which facilitates informed public planning adapted to complex realities of technological diffusion processes.

The rest of the paper is structured as follows: Section 2 explores the literature on the topic. Section 3 presents a novel model based on agent-based simulation and IBR. A discussion of previous models and their comparison with the model presented in this paper is reported in Section 4. Section 5 details how the model is calibrated. Section 6 presents the experimental scenarios and results. Finally, Section 7 summarizes our contributions and gives some insights into future research directions.

2. Literature

2.1. Innovation diffusion

The analysis of the innovation diffusion (products or processes) allows the evaluation of new products or processes adoption rates, and it aims to provide information on the level of cumulative adopters over time, which is essential for operations planning. Fisher and Pry [10] along with Bass [9] empirically observed that innovation diffusion processes present a sigmoidal shape, with a growing percentage increase in the early periods but decreasing in later stages. Each of these works presents a way of modelling and analyzing diffusion processes. Fisher and Pry [10] propose the following ad hoc functional form with a single parameter:

$$\frac{f}{1-f} = e^{2\alpha(t-t_0)} \tag{1}$$

where f represents the percentage of adoption, α is the fractional growth rate and t_0 is the moment at which $f = \frac{1}{2}$, while Bass [9] extends Rogers' [27] previous work on innovation diffusion, which classifies adopters as *innovators*, *early adopters*, *early majority*, *late majority*, and *laggards*. This approach implicitly recognizes the importance of social relationships in innovation processes, as an imitation process (social pressure), modelling the number of adopters at time t as a linear function of the number of previous adopters and the number of those who have not yet adopted. This is formalized as:

$$\frac{dN(t)}{dt} = p\,(m - N(t)) + \frac{q}{m} N(t)(m - N(t)). \tag{2}$$

where p, q, and m are constants and $N(t)$ is the previous number of adopters. Constant p is the probability of adopting "without external stimulus" and its magnitude reflects the importance of "early innovators" as defined by Rogers [27]. Constant q reflects the pressure that imitators receive from agents who have already adopted. Constant m represents the total number of agents in the social system.

The advantages of these simple models and their extensions are [28]: i) they make easily understandable assumptions that hardly allow unconscious manipulation by the analyst; ii) are easy to interpret and; iii) can be applied to a wide variety of circumstances [10]. However, these models can only explain innovation diffusion processes in a posteriori fashion (ex-post), which excludes their use as predictive tools. Furthermore, they are based on imitation as a relationship between previous adopters and those yet to be adopters, although the causes of such imitation are not studied in more detail, i.e. the existence of mutual influences are implicitly assumed. The innovation process is considered a competitive substitution of one product or process for another; innovation success is justified on the premise that a product or process to be introduced for the first time is less developed than existent products or processes it competes against and, therefore, it is likely to have the greatest potential for improvement and cost reduction. On the other hand, both models assume that there is a small percentage of the available market that emerges spontaneously (innovators). If this percentage reaches a value of 10 % the viability of the innovation is considered proven, even without the improvement and cost reduction that will come with it, increasing the volume, so guaranteeing the innovation diffusion.

Despite their restrictions, these two models are the most widely used paradigms for forecasting innovation diffusion [29–31]. However, their construction as ex-post models makes predictions difficult, and these must be based on estimates of parameter values from previous "similar" diffusion processes. Massiani and Gohs [32] make an in-depth analysis of the literature regarding the difficulties in predicting the diffusion of new products by assigning values to the parameters from previous processes, and state that the prediction estimates with this methodology are arguable and widely variable. The aggregate information handled in these models questions the fact that in different diffusion processes, all the conditions that facilitated it are maintained.

This work closes this gap in the above models of innovation processes and proposes a justification to consider agent behavior. Modelling using ABM makes it possible to anticipate the dynamics of the innovation diffusion process based on the characteristics of the product or process, the agents, and their interrelationships in the market. This analysis provides relevant information for operations planning, anticipating the efforts needed to overcome resistance to innovation and the most efficient way to do it.

2.2. ABM

The computing development has made it possible to carry out classical theoretical analyzes such as input-output models [33], macro models [34], linear programming [35,36], and computational models of intra-organizational behavior [37] to be used with large amounts of data, evaluating them in an increasingly interrelated and changing reality. The great advances in computing in recent years add simulation to the research techniques to be expanded, and within this, agent-based simulation has proven to be very useful as a way of enriching the less realistic aspects of classical theories [38]. Currently, it is possible to easily represent individualized rules of action and relationships among agents, providing the consequences for the whole, and obtaining results that, previously, were analytically intractable.

ABM models present a population of agents located in a social environment of interaction [5,39–42]. Agents behave according to explicit rules and interact with each other through networks (as representations of social, spatial, or physical relationships), which can be exogenously specified or generated through endogenous relationship rules. From the agents and their interactions, the models can produce local or general equilibria, even perpetual dynamics of change (some of them very surprising and consistent with real situations), establishing a bottom-up structured methodology. In biology, physics, or chemistry, it is already common to formulate theoretical models based on properties of particles or substances and their interrelationships that are later contrasted with reality (modeling cells in Karr et al. [43]; modelling of chemical compounds of medical importance in Lewars [44]; modelling of flow fields in Hoffman and Johnson [45]).

In this work, we describe a new model (ASPID) based on the stylized parameters that determine agent decisions. Knowing a few agent parameters and the network of links makes it possible to anticipate the time needed to change equilibria. ABM models deal with stochastic aspects naturally, evaluating the elements that affect the probabilities of the aggregated states. The distribution properties of agent states can be characterized by running a specific model multiple times and allowing random seeds, decision rules, or relationships to vary [46,47].

2.3. Intentional Bounded Rationality (IBR)

We propose a new explanation of innovation diffusion processes based on the Intentional Bounded Rationality (IBR) theory of agents. This approach allows agents to make errors in their judgments due to cognitive limitations in information processing [48,49]. The IBR proposed by Sáenz-Royo, Chiclana, and Herrera-Viedma [50] aims to close the gap between the representation of agent behavior and the mechanisms that govern human cognition. Its functional form collects the way to decide, allows agents to make mistakes in a systematic way (they make mistakes by choosing alternatives in which the agent considers that it is not worth managing more information), and it is efficient in the sense that it does not model aspects of behavior unnecessary to understand the decision of agents. The IBR establishes the regularities of the probability of agents opting for an alternative, combining a priori probabilities (such as beliefs prior to the information being processed) and differential performances of alternatives. In addition, each agent has a degree of ability to process information that allows them to anticipate the performance of their decision with greater or lesser precision.

In the IBR, the fallibility of agents is not the result of noisy information signals [51,52], but rather the relationship between the difficulty of the decision and their limitations to process information [24,53]. The intentionality is reflected in the existence of an inverse relationship between the error committed and the difference in the performance of the status quo (current technology) with respect to the innovation. The less difference in performance between the innovation and the status quo (less contribution from the innovation), the more inaccurate the agent's analysis will be and, therefore, they will make more mistakes. The IBR conceptual framework assumes that all information is available, and the agent, according to their characteristics, decides how much information to process. Different decisions by agents may be due to the possible different abilities they have to process information or because, even when having the same ability, they have chosen to process different signals [54,55].

2.4. Social system networks

Social ties can come from formal relationships (communication channels consciously established by organizations or collectives) or informal relationships (agent-chosen social ties) and are important when decisions are interdependent. Two important features of social ties are 'centrality' and 'density' since changes in them substantially alter *ceteris paribus* social system outcomes [56].

Relationship networks and their impact on the speed of diffusion have been especially used in contagion models (see the review by Brauer and Castillo-Chávez [57]). These models are very similar to those for innovation diffusion, where the contagion possibility depends on the distance between an infected person and another who is not, within a given network. Variations of contagion models in network structures have been applied to the study of learning/knowledge acquisition [58–60] and research findings show that the knowledge distribution depends on the structure of networks connections between groups [61–64]. Another relevant research question is how the network structure influences the balance between staying in the status quo (exploitation using known solutions) and finding new solutions (innovation) [21,65,66]. We share with these previous works the interest in examining the influence that the structure of relationships exerts on the results of the social system, in our case, the probability of successful adoption and on the time necessary for this to occur. However, while network-based contagion diffusion focuses on establishing a dynamic of knowledge sharing or performance, our work focuses on how decisions are made by agents and how the network structure affects decision-making. Many authors [5,67–70] claim to increase research on innovation decisions as a fundamental step to understanding performance and the evolution of the innovation diffusion process.

When agents participate in decisions, they are aware of the actions of others, and their social ties make social influence possible [56]. Innovation diffusion models must account for these interdependencies in the manifestation of agent judgments [71,72] since social ties allow information to be transmitted and discussed. Salas-Fumás, Sáenz-Royo, and Lozano-Rojo [25] add to the opinions of agents that the organizational environment influences the probability of their position, connecting organizational interdependencies and agent judgment. In this paper, innovation diffusion also takes place in a network so that, at each point in the network, the mutual influences for or against the innovation may differ, as well as the probability of supporting the innovation. *Social influence* can be understood as the weight of environmental judgment in one's mind [73–75]. This means that the probability of an agent adopting an innovation increases with the relative number of agents who have previously adopted it within their social network [25]. Bounded rationality makes agents sensitive to other judgments because they are uncertain of their own judgment [76] justifying imitation as a feature of bounded rationality consciousness that makes agents fallible. Therefore, the density of the network strongly influences agent judgments and can change the speed and resistance of the diffusion of innovations [5,77].

3. ASPID model

Let us suppose a set of N agents (nodes) connected to each other through a social network (i.e., there is a path between any pair of nodes)

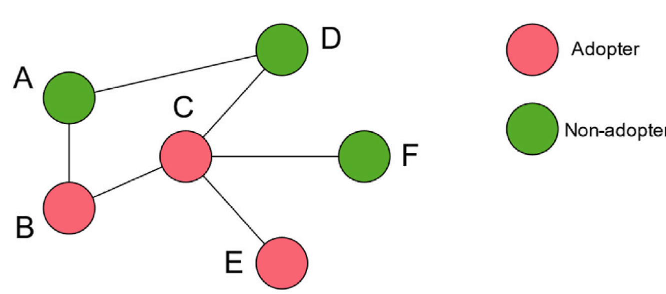


Fig. 1. Example of innovation network.

(see Fig. 1). Let $V_s \in \mathbb{R}$ be the latent performance for agent i operating with the dominant technology (status quo). On the other hand, let $V_c \in \mathbb{R}$ be the latent performance for agent i for a certain innovation.

The ASPID model distinguishes two linked processes: stimulation and decision. Stimulation precedes and triggers the decision. Without stimulation, there is no decision.

3.1. Stimulation

Agents do not question the status quo (the technology used) until they perceive a stimulus. A stimulus is defined as the agent's perception that there is an alternative technology that may perform better than the one currently being used, which forces them to rethink their situation (reflect) and decide about whether to continue with the technology or change it. This approach differs from classical models, which adopt develop an imitation process, such as a one-way accumulation, to adopting the innovation.

The nature of the stimulus is binary; that is, an agent may or may not be stimulated during a given period. The stimulus is temporary and non-persistent; it does not accumulate or store; it is a one-time event that triggers a process of reflection and decision. The stimulus can be repeated in successive periods; therefore, an agent can receive multiple stimuli over time, but only one per period.

The stimulus can be external or internal to the relationship network. External stimuli come from information disseminated through the media, social networks, and advertising systems. Internal stimuli come from the agent's immediate environment and are the result of a decision made by an agent within their environment of influence. External stimuli are much less intense than internal stimuli because they present passive information, meaning they do not allow interaction, and represent self-serving information. Internal stimuli instead allow facilitates discussion between agents that allows for an exchange of information; the internal stimulus has been modeled as a word-of-mouth process. The internal stimulus affects two agents who question their previous decisions, and both may change their decisions, neither may change it, or only one may change it. Thus, in Fig. 1, the stimulus could be contact between A and B, contact between C and D, or contact between C and F.

3.2. Internal stimulation-decision (word-of-mouth)

Word-of-mouth stimulation-decision assumes that each agent can only have contact with one discordant agent per period, and the contact will be chosen randomly from among those in its social environment. In each period, all discordant agents with the possibility of contact do so. In Fig. 1, stimulus A with B is obligatory, and C must stimulate either D or F, but not both. The choice between D and F is random.

3.3. Decision

After the reflection process, four cases can occur, as depicted in Fig. 2: the two remain as they are (the adopter and the status quo); the old adopter adopts the status quo and the agent from the status quo innovates; both acquire the innovation; or the two go on to use the status quo.

The functional form of IBR decision-making establishes that agents must anticipate the latent performances of both (V_s, V_c), the information processing capacity and the complexity of the processed information are combined, along with their beliefs and mutual influences. The probability of innovating for the agent over time is proportional to the relative weight of the normalized performance of the innovation concerning the normalized performance of the status quo. Eq. (3) formally defines this probability:

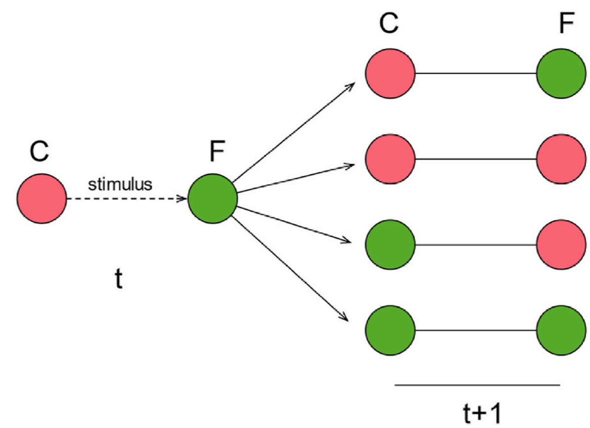


Fig. 2. Possible network state after stimulus and reflection.

$$p_i = \frac{p_i^0\, nc_j e^{\beta_i \frac{V_c}{V_c+V_s}}}{\left(1-p_i^0\right) ns_i\, e^{\beta_i \frac{V_s}{V_c+V_s}} + p_i^0 nc_j\, e^{\beta_i \frac{V_c}{V_c+V_s}}} = \frac{1}{1+\frac{ns_i\left(1-p_i^0\right)}{nc_j p_i^0}\, e^{\beta_i \frac{V_s-V_c}{V_c+V_s}}} \quad (3)$$

Where p_i^0 and $\left(1-p_i^0\right)$ are the probabilities a priori (beliefs prior to information processing) of accepting innovation and remaining in the status quo, respectively, that is, the emotional influence on the choice, at time t. Fig. 3 describes the Markov chain between the two states (status quo (S) and change for innovation adoption (C)).

Following up eq. (3), the difference in normalized performances, $\frac{V_s-V_c}{V_c+V_s}$ indicates that the probability of the agent to accept the innovation increases when the difference between its latent performance and that of the status quo increases, that is, the greater the difference in the latent performances of innovation and the status quo, the greater the probability of choosing to innovate.

The parameter β_i is interpreted as a measure of the agent's ability to process information, i.e. the specific knowledge the agent has about the status quo and the innovation. When β_i decreases, the weight of the probability tails increases, making it more difficult for the agent to anticipate the difference in performances. When $\beta_i = 0$, the probability of choosing the status quo or the innovation is performance-independent, since the agent is unable to anticipate the performance for either of them, that is, the decision is made randomly, resulting in $p_i = .5$. A value of $\beta_i > 0$ corresponds to "intentionally rational" decision-makers who attempt to choose the best option. To reduce the probability of error, more information must be processed. The decision maker will only reduce the probability of error if the cost of processing more information (in terms of effort and resources) is lower than the improvement in the expected performance due to the reduction in error. Higher positive values of β_i represent that the agent's expertise significantly increases the probability accuracy in the decision-making, even when differences in performances are small. Eventually, as β_i tends to infinity, the probability of error converges to zero, which is true even for small relative differences between the status quo and the innovation.

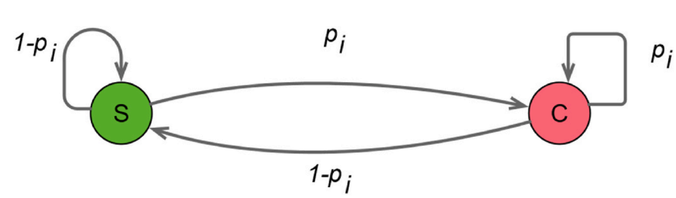


Fig. 3. Markov chain for status quo and innovation adoption states.

3.4. Word-of-mouth diffusion process

If agents do not receive a stimulus that questions their choice, then they do not consider changing their status. Assume that at the initial (first) period of the appearance of the innovation a commercial action is carried out (external stimulus) contacting X agents (potential 'innovation adopters'). The agents who receive the external stimulus at the first period (seeds) must reflect on the possible performance of the innovation with respect to the status quo technology. The decision-making IBR functional form states that agents must anticipate the latent performances of both the status quo (V_s) and the innovation project (V_c). To obtain the probability of a stimulated agent choosing to adopt the innovation (with a latent performance V_c), the ability to process information and the complexity of the information processed are combined, along with their beliefs and mutual influences. If any of the agents initially stimulated adopts the innovation, a word-of-mouth process in the social system (network) begins in which the stimulus for reflection occurs when two connected agents use discordant technologies (one the status quo and the other the innovation). At each period, agents connected with discordant agents must contact only one of them selected at random. This process assumes a Markov chain and is repeated until consensus is found around the status quo or innovation in the social system, that is, it is repeated until all agents use the same technology.

Let be a process of word-of-mouth diffusion in which an agent i using the status quo technology contacts an agent j using the innovation. Then there is a stimulus conveyed from j to i in which both agents reflect. As per eq. (3), the probability of innovation for the agent i at time t is proportional to the relative weight of the normalized performance of the innovation with respect to the normalized performance of the status quo; the variable ns_i represents the number of agents connected to i using the status quo technology; the variable nc_j stores the number of agents connected to j using the innovation; the ratio $\frac{ns_i}{nc_j}$ will determine the weight of mutual influences in the decisions of agents. This formalization of mutual influence can be extended to apply this model for social systems (networks) represented as directed graphs to associate each agent in the network with different weights by specifying $ns_i = 1 + \sum_{k=1}^{K} \rho_{ik}$, where ρ_{ik} represents the influence of agent k (using the status quo) on agent i.

During the contact process between two dissenting agents, the probability that i accepts the innovation is p_i and that of remaining in the status quo is $1 - p_i$, while for agent j the probability of switching to the use of the status quo technology is $1 - p_j$ and that of continuing to use the innovation is p_j. Notice that when $\beta_i = \beta_j$, both agents are assumed to have the same level of expertise and, if there are no prior beliefs in favor of any alternative, or if the beliefs of both agents are the same ($p_i^0 = p_j^0$; $1 - p_i^0 = 1 - p_j^0$), then the probabilities of adopting the innovation of agent i and j are equal ($p_i = p_j$) as it is the probabilities of opting for the status quo technology ($1 - p_i = 1 - p_j$).

The dependent variables in the model allow us to set up different scenarios. Those variables are: i) the performance level of the innovation against the status quo; ii) the agent level of expertise; iii) the agent's beliefs, and iv) the network topology of the social system. The independent variables are: i) the time required for the system either to converge to the innovation adoption or to remain with the status quo technology, and ii) the probability that both types of convergences occur. The ABM model allows for running simulations of different scenarios to explore how the diffusion process works step by step. The simulations shape the different possible paths resulting from the representation of stochastic individual decisions. The classical models provide only an average behavior of the agents. In contrast, the variability of ABM-based simulations shows many of the possible results that can occur with the same initial hypotheses (as is the case in reality), showing the model's level of uncertainty. The dispersion of the simulations around the average provides information on the composition of the variance, which is relevant for operations management.

This conceptual framework makes it possible to evaluate ex ante the results obtained from any innovation process once the agents and the network have been characterized. The process is sensitive to the agents' cognitive capacity, that is, asking the right questions, obtaining information, and processing it according to logical reasoning to finally get a decision. IBR assumes that the more information that is processed, the lower the probability of error in the decision. A larger difference between the latent performances of alternatives allows selecting the best option. As it occurs in real world scenarios, in many cases agents choose without thinking deeply (apparently irrationally) and hesitate when objections are raised. Agents hold prejudices and beliefs (p_i^0 and $1 - p_i^0$) which are combined with information processing ($e^{\frac{\beta_i (V_s - V_c)}{V_c + V_s}}$). The reflection processes require time and effort to carry out logical reasoning and thereby improve the parameter β_i.

The way in which the innovation spreads through the network has effects on its final acceptance or rejection. Spatial aspects such as where the process begins can change the probability of adoption since the environment influences the behavior of the agents. This approach assumes that there is always a certain possibility of resistance to adopt the innovation. The seeds initiate the word-of-mouth diffusion and create the possibility that their neighbors overcome their resistance regarding the innovation, in an iterative way. Our approach sheds light on how these dynamics play out, and it aims to trace how the innovation diffusion takes place.

Our model assumes that innovation can outperform (or underperform) the status quo technology and that agent decision-making mechanisms affect the types of errors that appear in the aggregated social payoff. If the social system rejects an innovation that provides higher performance than the status quo, it will be an omission error and will have an opportunity cost. If the social system accepts an innovation that performs less than the status quo, it will be a commission error and represents a real cost.

Social systems can generate adverse dynamics to agent decisions by linking agent performance to the communication structure, untying the result from the relative goodness of the innovation. Networks rely on natural mechanisms of communication and cohesion that can prevent the diffusion of profitable innovations, or the excessive optimism of some agents acting from leading to the adoption of performance-reversing innovations. This is modeled in our model via an agent's value of the performance of the members of their circle of influence ($ns_i = 1 + \sum \rho_{ik} | k \neq i$; $nc_j = 1 + \sum \rho_{jk} | k \neq j$). Our formalization gives them a value of one ($\rho_{ik} = 1$), when the performance of each one of the members of the circle of influence has the same weight as the performance of the agent (very cohesive group) ($ns_i = 1 + K$; K is the number of no adopters connected to i; $nc_j = 1 + K'$; K' is number of adopters connected to j), and zero ($\rho_{ik} = 0; \rho_{jk} = 0$) when the only performance that counts is their own showing themselves to be independent (a non-cohesive group) ($ns_i = 1; nc_j = 1$).

4. Discussion of Fisher and PRY, Bass and ASPID model

Fisher and Pry model [10] requires knowing the moment when half of the social system has adopted the innovation. With this information, the growth rate α can be estimated with eq. (1). The discretized time in periods marks the growth of adopters in the first phase of increasing growth (up to t_0) and later decreasing growth, imposing symmetry between the two phases. The α rate is limited to adapting the sigmoid curve to the time taken for the innovation diffusion process to take place.

In the Bass model two diffusion mechanisms are identified. The first mechanism allows agents to adopt the innovation according to their own experience and judgment, and we call it *Reflection*. In the second mechanism, agents adopt from the observation of the behavior of others, and we call it *Imitation*. Note that, technically, the modeling is with a differential equation that starts from a known number of initial adopter

($N(0)$), its parameters p, q and m are constant, and the scope of the diffusion of the innovation is reflected in the ratio $m/\,N(0)$. Knowing m is realistic since it is usual to have information about the number of agents who are using the technology of the status quo.

Reflection. In this case, a constant adoption speed is assumed, and it does not depend on the number of previous adopters and therefore there is no imitation, $q = 0$ and $p > 0$, and the model becomes:

$$\frac{dN(t)}{dt} = p\,(m - N(t)) \tag{4}$$

It is assumed that throughout the diffusion process, a constant percentage of agents (p) using ($m - N(t)$) adopt the innovation. $N(t)$, which presents an increasing temporal shape but at a decreasing rate, is

$$N(t) = m - (m - N(0))e^{-pt} \tag{5}$$

Imitation. In this case, regarding those pending adoption ($m - \ N(t)$), it is assumed that ($\frac{q}{m}$) who have been influenced by agents who in turn have already adopted the innovation at period t ($N(t)$) where $q > 0$ and $p\ = 0$, and the model becomes:

$$\frac{dN(t)}{dt} = \frac{N(t)(m - N(t))q}{m} \tag{6}$$

Eq. (6) indicates a relationship of continuity between the dispersion of the population (between those who adopt the innovation and those who stay attached to the status quo technology) and the evolution of imitation, which can be rewritten as follows:

$$\frac{dN(t)}{dt} = \frac{N(t)}{m}\,\frac{m - N(t)}{m}\,mq \tag{7}$$

where $\frac{N(t)}{m}$ and $\frac{m-N(t)}{m}$ are the respective probabilities of finding an agent using the innovation or the status quo technology, respectively, at each period. The product of both terms is the variance at each period. Imitation increases (or decreases) according to the dispersion of the population, causing a process like that proposed by Fisher and Pry. The functional form of $N(t)$ obtained by solving the above differential equation is

$$N(t) = \frac{m}{1 + \frac{m-N(0)}{N(0)}e^{-qt}} \tag{8}$$

The time profile of $N(t)$ is also increasing, but now the increase rate is first increasing and then decreasing as in the case of Fisher and Pry.

The complete model by Bass given in eq. (2) involves positive parameters $p, q \in \mathbb{R}^+$ to reflect the ability of agents to adopt innovation by *Reflection*, as an exogenously acquired element, and by *Imitation*, which depends on the number of previous adopters. The relative importance of each component of the process in a particular social system is an empirical question, and the functional form of the complete model $N(t)$ is

$$N(t) = m\frac{1 - \frac{\frac{m-N(0)}{\frac{p}{q}m+N(0)}p}{q}e^{-(p+q)t}}{1 + \frac{m-N(0)}{\frac{p}{q}m+N(0)}e^{-(p+q)t}} \tag{9}$$

Bass model gives a diffusion shape that is first convex and, after an inflection point, becomes concave (sigmoidal curve). Its graphical shape is like *Imitation* (eq. (6)), but the resulting functional shape is more flexible because it has two fit parameters, p, and q.

In the models by Fisher and Pry and in Bass, the adopter percentage depends on the time and the acceptance rates (α in Fisher and Pry; p and q in Bass). Moreover, Bass model introduces the number of agents pending to adopt ($m - \ N(t)$) and the number of adopters ($N(t)$). Assuming a complete graph representing the communication network (i.e., all agents are connected to each other), it is implicitly granted that all agents pending to adopt can be stimulated and once they adopt, they cannot go back to the technology of the status quo.

Applications of Bass model to social networks establish an imitation rate q [78,79]. When the social system communicates through a complete network (everyone communicates with everyone) closed diffusion equations can be obtained from the extensions of the Bass model that are defined discontinuously:

$$N(t) = \begin{cases} N(t-1)(1+q) \mid N(t-1) > m - N(t-1) \\ (m - N(t-1))(1+q) \mid N(t-1) < m - N(t-1) \end{cases} \tag{10}$$

When the number of agents is very large, the only limitation for the diffusion process is to obtain a stimulus (word of mouth process) and the imitation rate q. If the social system is a complete network, then the diffusion equation is $N(t)\ = N(0)(1+q)^t$. This formulation represents a geometric progression of ratio $(1 + q)$ for each period, that is, for each agent that uses the innovation, a rate q of agents that adopt it is influenced. This functional form is equivalent to that of Bass when there is only *Imitation* and there is no upper limit on the growth, i.e. $\frac{dN(t)}{dt} = qN(t)$ which has solution $N(t)\ = N(0)e^{qt}$. The difference between the two equations is that Bass approach is continuous from a temporal point of view, that is, it considers that at each period t there have been infinitesimal contacts that led to subsequent contacts $e^q\ = \lim_{n\to\infty}\left(1 + \frac{q}{n}\right)^n$.

In the case when each agent who uses the innovation influences one who uses the status quo, the rate of those who imitate is 1:1 and $q = 1$ (each contact implies an imitation), and the diffusion equations become $N(t) = N(0)e^t$ (for Bass' original model) and $N(t) = N(0)2^t$ (for the complete network model). Social networks provide information that Bass does not and resolves it by assuming continuity in the dissemination process.

The functional form of the IBR agents model proposed in this work has important similarities with Fisher and Pry model and Bass model. Indeed, avoiding social influence ($ns_i\ = 1; nc_j\ = 1$) and if agents have no biases ($p_i^{0,c}\ = p_i^{0,c}\ = \frac{1}{2}$), eq. (3) resemble, respectively, Fisher and Pry model and Bass *Imitation* model:

$$\frac{p_i}{1 - p_i} = \frac{e^{\beta_i\frac{V_c}{V_c+V_s}}}{e^{\beta_i\frac{V_s}{V_c+V_s}}} = e^{\beta_i\frac{V_c-V_s}{V_c+V_s}} \tag{11}$$

$$p_i = \frac{1}{1 + e^{-\beta_i\frac{V_c-V_s}{V_c+V_s}}} \tag{12}$$

The reader should keep in mind that these sigmoid shapes of our model represent the agent behavior with regards to the performance differential, instead of the behavior of the system as a whole.

Our model is based on the probability of agent adoption of the IBR, and it depends on the additional performance that the innovation provides over the status quo and on the ability of the agent to appreciate it. Therefore, the speed of diffusion of the system not only depends on the probability of agent acceptance but also on the structure of the network, justifying that many innovations do not progress in their diffusion process, maintaining the status quo technologies. In our model, the network structure limits the appearance of the stimulus that activates reflection (the possibility of making another decision) and gives meaning to the two intuitions of Bass model, on the one hand, *Reflection*, as an agent evaluation who tries to anticipate innovation performance compared to the status quo, and on the other, *Imitation*, as an influence of the environment on agent evaluation and decision. The stimulus and social influence (imitation) are separated and, although both are linked to the network underlying the social system, their consequences can be obtained separately. Another important difference is that in our model agents can change technology as many times as they want with no other limitation than receiving a stimulus that questions their previous decision.

As happened in social network extensions of Bass model (eq. (9)), the proposed ABM model, whether the network has a small number of agents and is complete, presents the below closed equation with $N(t) = m - N(t)$:

$$N(t) = \begin{cases} N(t-1)(2p_i) \mid N(t-1) > m - N(t-1) \\ N(t-1) + (m - N(t-1))(2p_i - 1) \mid N(t-1) < m - N(t-1) \end{cases} \quad (13)$$

From equations (10) and (13) it is possible to obtain the equivalence between Bass imitation rate and the probability of acceptance in the ASPID ($2p_i = (1+q)$) being the social network extensions of Bass model a particular case of the model proposed here with the restriction that an agent can only shift towards innovation and never towards the status quo technology. In populations large enough in which growth is not limited, the diffusion function can be rewritten as $N(t) = N(0)(2p_i)^t$, assuming that agents are rational ($\beta = \infty$) and know when to adopt the innovation ($p_i = 1|V_c > V_s \,\forall i$). The only limitation of the diffusion process is to obtain a stimulus (word of mouth process), resulting in the closed equation of the behavior of the social system as a function of time $N(t) = N(0)2^t$.

If one wants to know exclusively the imitation process the proposed ABM model, the restriction that should be established is that agents are incapable of processing information ($\beta = 0$), so their decisions will be guided by the actions of their environment, transforming eq. (3) to $p_i = \left(1 + \frac{ns_i}{nc_j}\right)^{-1}$. Imitation in our model depends on the number of agents using the innovation or status quo in the settings of the discussing agents. Assuming the communication network is complete, the equation can be rewritten as $p_i = \left(1 + \frac{m-N(t)}{N(t)}\right)^{-1} = \frac{N(t)}{m}$. Now the imitation proposed by Bass remains as a particular case, distinguishing between a decision problem and one of the mutual influences, with the equation of the diffusion process without population limit being: $N(t) = N(0)\left(\frac{2N(t)}{m}\right)^t$ when the adoption of any of the two technologies is freely allowed, and $N(t) = N(0)\left(1 + \frac{N(t)}{m}\right)^t$ when it is accepted that agents can only change in one way (from status quo to innovation).

When the system leans on communication network topologies other than a complete graph, the diffusion process can be represented by a Markov chain and, in general, a closed equation for the joint behavior of the system cannot be obtained, which implies that the process must be simulated.

5. ASPID ex-post analysis

Models do not explain exactly how the world works since they are built on ideal assumptions and the most significant elements in the causality of relationships to model to facilitate analysis and allow for conclusions that are easy to imagine and analyze. A simple approximation can be so coarse that it may be empirically very inaccurate, but valuable because it may lead to achieving a solution that would otherwise be mathematically intractable. Thus, the level of abstraction in modelling must balance the detail of its closeness to reality and its operational value. Simplicity, as a necessary imperfection, is part of a solid design of models: starting from the essential parts and later relaxing the assumptions and enriching the information, gradually giving the model greater fidelity to reality. Axtell and Farmer [38] show how research in economics has progressed thanks to works that replace one or two of the standard assumptions, generating conclusions that cover the initial ones but that may present results that differ from the usual specifications.

The innovation diffusion presents quantifiable aggregate patterns identified by classical models. To delimit the parameter search space of our model, different calibration and estimation techniques can be used. One of the most widely used approaches in ABM is to align the model with classical outputs from aggregated data [38]. The model obtains a fixed reference point that allows the analysis of the balances of the different combinations of parameters in the aggregated result and demonstrates its capability to adjust aggregated data for the ex-post analysis.

Bass model is a dominant forecasting paradigm in the diffusion of innovations [32], and therefore it is chosen to calibrate the agent acceptance probability, which is compared with the estimate obtained with Fisher and Pry model. Calibration follows an inverse process to the ex-ante estimation, first estimating the value of the agent probability that produces the observed behavior, to later evaluate the greater microscopic complexity that this probability can produce. Enriching the combined features allows us to get closer to reality, which makes the analysis difficult.

ASPID is tested with three estimates of the Bass model for electric vehicle adoption, normalizing the market size (in Massiani and Gohs [32]). The adoption of electric vehicles has been a significant public policy initiative of the European Union. Estimates: Gross [80] ($p = 0.01$, $q = 0.1$); Becker et al. [81] ($p = 0.025$, $q = 0.4$); Massiani y Gohs [32] ($p = 0.0032$, $q = 0.8591$). The forecast ranged from the most pessimistic (Gross) to the most optimistic (Massiani and Gohs). It is intended to replicate Bass model through the Fisher and Pry model, and the ASPID model when the communication between agents is a complete network, distinguishing between the ASPID model restricted to only be able to change towards innovation (eq. (10)) and the unrestricted ASPID model (eq. (13)). Using the Generalized Reduced Gradient (GRC) technique [82], the parameters that best fit each model are obtained and illustrated in Figs. 4–6.

In Fisher and Pry model, the period at which 50 % of the agents adopt the innovation (t_0) and the adjustment parameter (α) that minimizes the squared residuals by GRC are obtained simultaneously. In the proposed ABM models with and without restrictions, the initial adopters ($N(0)$), the restricted probabilities (q_i) and the probability that characterizes the IBR (p_i) are estimated by GRC. The differences with the Bass model trajectory are a consequence of the fact that they are discrete models (reduce flexibility but closer to what occurs in the real world).

ASPID model allows for additional analysis. If the three systems are homogeneous in terms of agent expertise ($\beta = 1$), in the absence of mutual influences ($nc_j = ns_i = 1$) and without prejudice ($p_i^0 = 1 - p_i^0 = \frac{1}{2}$), the different values of the probability of acceptance indicate the difference in performance between the technology of the status quo and that of innovation. In Gross case, the probability of agent adoption is 54 %, which means that the performance of the innovation is around 20 % better than that of the status quo ($(V_s - V_c)/(V_s + V_c) = -0.2$); in Becker case, the probability of agent adoption is 66 %, which would mean a 68 % better performance agent of the innovation compared to the status quo; while in Massiani and Gohs case, the probability of agent adoption is 80 % and innovation performance outperforms status quo technology by 140 %. There is an expected relationship between Bass imitation parameter (q) and the restricted acceptance probability parameter (p_i) (see Table 1), since it is the extension of the model to social networks.

Fisher and Pry model and ASPID model both fit extraordinarily well to the shapes proposed by the different parameters of the Bass model, presenting coefficients of determination greater than 0.997. The comparative graphs of the three figures show minimal differences between the models, which guarantees that our generalization can obtain good estimates ex-post. Lastly, it should be noted that discrete models can adapt worse to continuous models, but the possibility of detailing the composition of their elements allows them to be better adapted to the reality of the processes. This section has focused on verifying whether the general model is acceptable in ex-post estimates by providing an initial calibration, but its central task is to provide realistic ex-ante predictions. The ASPID model allows a more extensive analysis if there is available information about the capacities and the network of agents that have intervened in the diffusion of innovation.

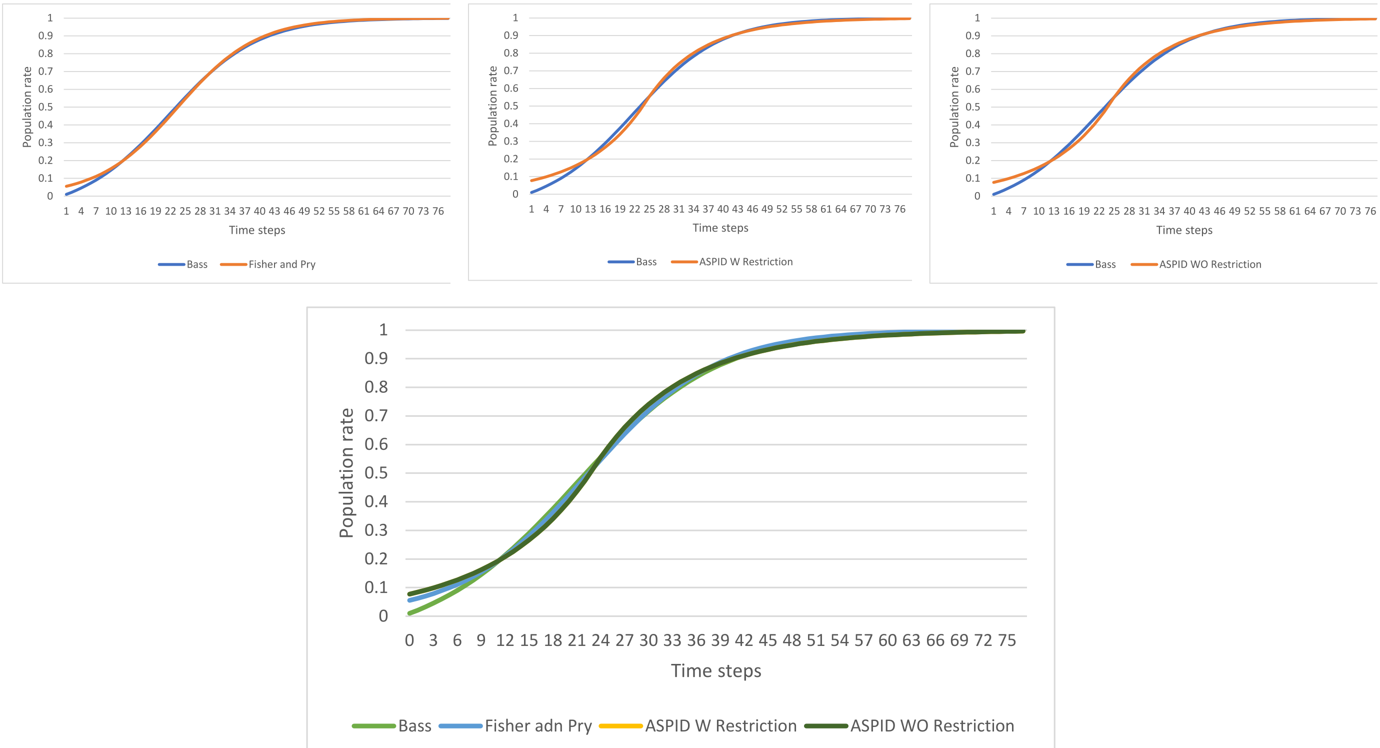


Fig. 4. Estimation of Fisher and Pry model, ASPID With Restriction and ASPID WithOut Restriction with respect to Bass model with Gross parameters.

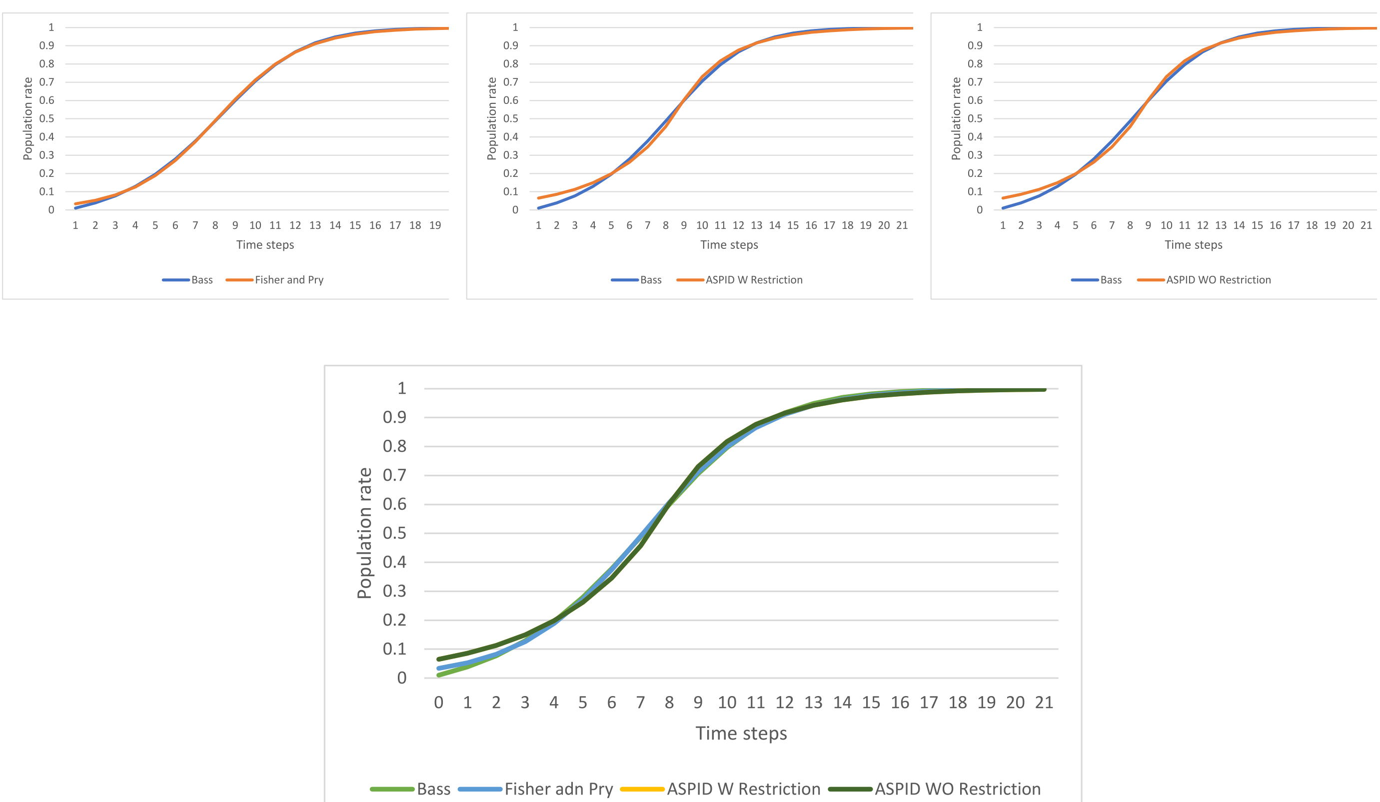


Fig. 5. Estimation of Fisher and Pry model, ASPID With Restriction and ASPID WithOut Restriction with respect to Bass model with Becker parameters.

6. ASPID ex-ante analysis

The ASPID model differs substantially from classic models. The incorporation of the IBR in the agents' decision-making justifies conceptually the *Reflection* Bass stage. This conceptual framework relates the difference in latent performances, the degree of experience, and

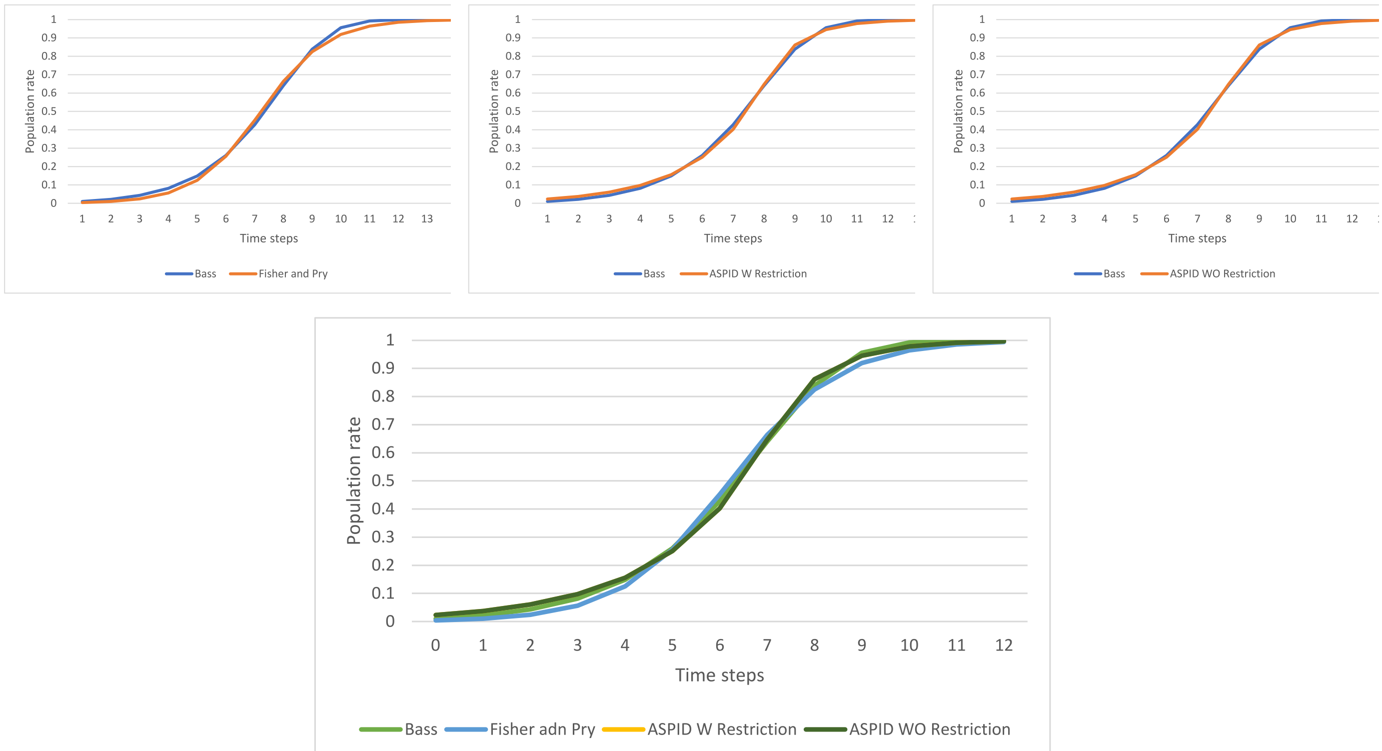


Fig. 6. Estimation of Fisher and Pry model, ASPID With Restriction and ASPID WithOut Restriction with respect to Bass model with Massiani and Gohs parameters.

beliefs, with the degree of agent error. Another contribution is that the model details between stimulus and influence, aspects that the Bass model reflects together as *Imitation;* this allows us to study how the network of relationships can affect the innovation diffusion. The ASPID model details the mechanisms by which the network of relationships can affect the diffusion of innovations. These aspects are crucial to allow ex-ante analysis.

Advances on technological developments that allow large amounts of information to be stored at reasonable costs [83] enhance importance of models that use detailed agent information since as much of the information they require may be possible to be incorporated into "'micro-data-bases". Business interest in microdata storage recognizes the value of the heterogeneity present in social systems [84]. Social media data is a good example. ASPID model can make use of previous models for the estimation of some elements: the evaluation of the performance of the status quo and that of the innovation can be carried out through a discrete choice model [85,86]; the calibration of agent skills can be done with Camerer and Hua Ho model [87].

When detailed information about agents is available, simulations allow valuable ex-ante analyses to plan resources to spread an innovation [88]. Simulations quantify the risk level of adoption and provide information on the composition of its variance. In fact, simulations that present random walks with different characteristics can present the same variance value. Large infrequent errors can provide the same variance as many small-value errors. However, the management of these two patterns must be different.

This section puts forward three different groups of experiments. The first group of experiments analyze how the agent's adoption probability in our model (p_i) affects the innovation diffusion; the second group of experiments measure diffusion evolution with different network topologies; the third group of experiments test our model by setting up scenarios with different number of agents.

6.1. Probability analysis

This group of experiments aim to test if changes in the probability of adoption (p_i) affect somehow the innovation diffusion process. Table 2 shows the model setup for probabilities in the range [0.55, 0.999999] with steps of 0.05 when the latent performance of innovation changes (increasing performance – increasing probability of adoption). Other important parameters of the simulation scenarios for this group of experiments are the population size (set at 100 agents) and the network topology.

Results of the 100 runs of the agent simulation are shown in Fig. 7 in grey with the red line representing the average result. As expected, p_i result in slower adoption. Darker lines and markers denote a higher frequency of these values. The percentage of successful innovation diffusion processes (out of 100 runs) are presented in brackets.

Diffusion processes with less than one hundred percent success have a sigmoidal shape, that is, they have a first section with a positive second derivative (T1), an inflection point (PC) and a second section with a negative second derivative (T2). When the time diffusion is long (low p_i), it can be seen how the T2 section is particularly elongated and, in some cases such as the graph with $p_i = 0.55$, the convexity of the T1 section is not apparent. The increase in the individual probability of accepting the innovation implies a change in the shape of the diffusion, from mostly concave to totally convex as can be seen in the graph with $p_i >= 0.9999$, losing the sigmoid shape. This assumes that the concave part is a consequence of latent performance of innovation. When latent performance of innovation increases, the diffusion of innovations is exponential and very fast.

The variance of the diffusion (different possible paths) also depends positively on the degree of the latent gain of the innovation. The dispersion around the mean shows a different shape above it than below it. Dispersion is low but very frequent above the mean, while it is high but rare below the mean. Therefore, managers should keep in mind that it is very likely that the diffusion shape is slightly above the mean, but it is also possible, though rare, that the diffusion shape is much below the

Table 1
Values of the estimated parameters of the models.

	Bass Model		Fisher and Pry			ABM W Restriction			ABM WO Restriction		
	p	q	T_0	a	Bass R^2	N(0)	rp_i	Bass R^2	N(0)	p_i	Bass R^2
Gross	0.01	0.1	22.5131187326007	0.0627932498517784	0.999125566229093	7.75698622978613	0.0856723865266533	0.997302274194247	7.75808718487099	0.542833713330123	0.997303191258849
Becker	0.025	0.4	7.08298733195228	0.236844390513525	0.999800022595064	6.49738710100484	0.321306980711069	0.998328184984843	6.4974702121092	0.660651673834451	0.99832813486657
Massiani and Gohs	0.0032	0.8591	6.22216494979705	0.436497597061947	0.999109436472995	2.33728559942652	0.606963223334668	0.999560135514417	2.33743893764109	0.803472534490466	0.999560157165382

Table 2
Parameter setup for simulation of different adoption probabilities.

p_i	V_c	V_s
0.55	10.20	10
0.6	10.40	
0.65	10.62	
0.7	10.85	
0.75	11.10	
0.8	11.39	
0.85	11.73	
0.9	12.20	
0.95	12.94	
0.99	14.59	
0.999	16.90	
0.9999	19.21	
0.99999	21.51	
0.999999	23.81	

mean. This aspect is important for developing contingency plans in operations management.

There is an obvious positive relationship between the increase in the probability of individual acceptance and the probability of dissemination success. Fig. 8 shows the evolution of the percentage of experimental runs (out of 100) in which all agents eventually adopt the innovation. This relationship shows concavity (negative second derivative), with small increments when p_i is close to 0.5 leading to large increments in the probability of success, while as p_i increases, the same increment in success requires larger increments of p_i. This result is consistent with the law of diminishing marginal returns.

6.2. Network topology analysis

This set of experiments aims to shed light on how the network topology of the system affects the innovation diffusion process. As we only vary the network topology models, the rest of the parameters of the simulation scenario will remain fixed for all the experiments. The parameters are set so that the agents make decisions independently (without social influence, i.e. $nc_i = ns_i = 1$), with a constant individual adoption probability ($p_i = 0.75$), values $V_c = 11.10$ and $V_s = 10$, and 100 agents with $\beta = 1$. In this specific configuration of no influence by social environment, the final success rate depends exclusively on the intrinsic quality of the innovation (represented by the value $p_i = 0.75$) and not on the structure of the network or the size of the system [25].

To evaluate the impact of network structure on the innovation diffusion process, we implemented various topological models widely recognized in the literature. The below seven laboratory network topologies were implemented (shown in Fig. 9).

(a) A complete network (CN), which allows direct communication between all individuals in the system.
(b) A Random Network (RN) with an average of 10 neighbors per agent to maintain a moderate connection density as a more realistic alternative to the CN.
(c) A network created with the Barabasi-Albert (BAN) model to represent the scale-free properties observed in numerous real-life social systems. The topology of this network follows a power-law degree distribution through a preferential connection mechanism, where agents with more connections have a greater probability of establishing new ties. In this implementation, a minimum of two neighbors per agent was established to ensure basic connectivity.
(d) A network with the Newman-Watts-Strogatz (NWSN) topology was created. This type of network is distinguished by combining short average path distances with high clustering coefficients. This implementation establishes an average of 10 neighbors per agent and a connection probability between nodes of 0.25 to

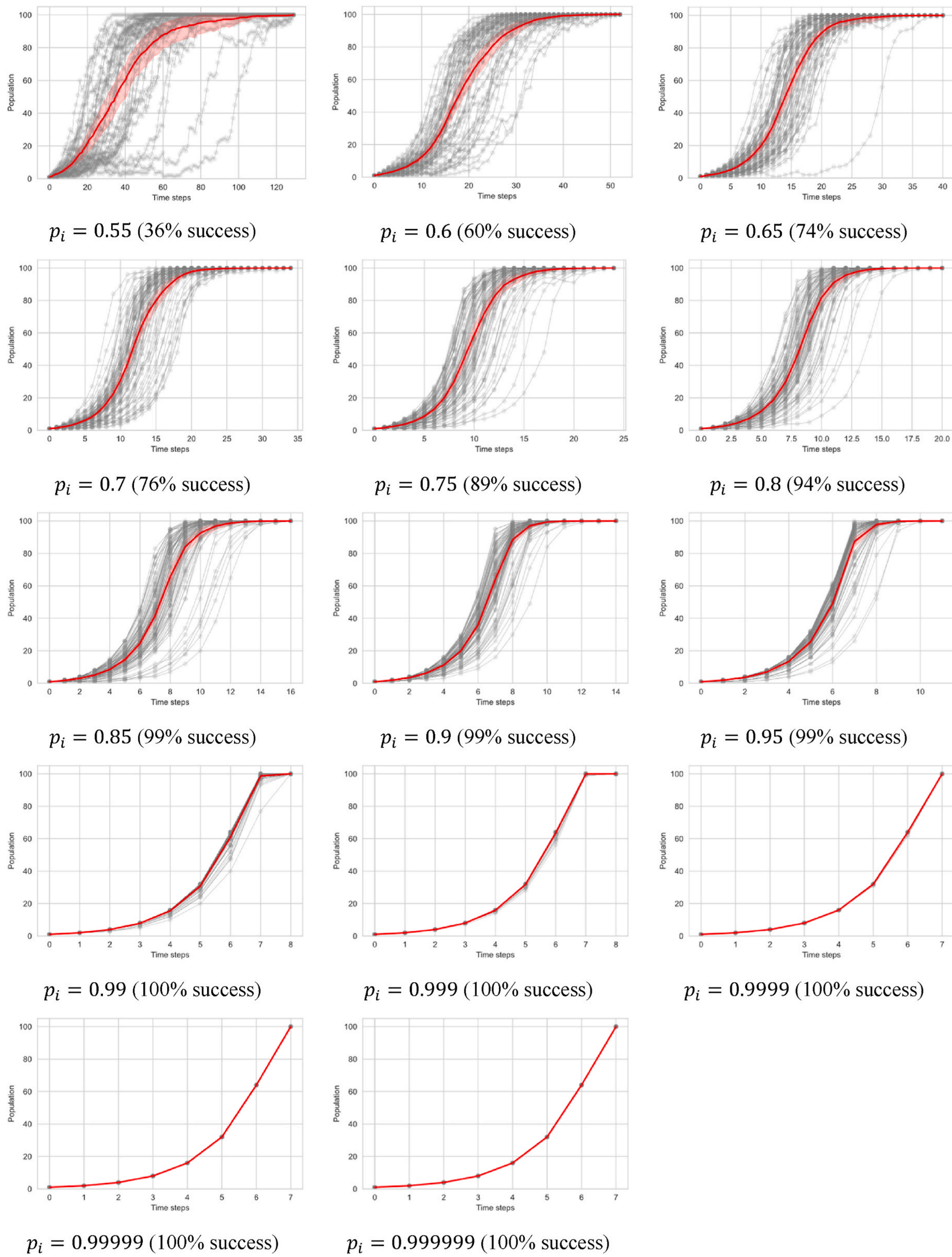


Fig. 7. Innovation diffusion with different values of p_i

guarantee the manifestation of small-world properties, fundamental to many social networks.

(e) A star network (SN) represents systems with centralized decision-making, where a central agent connects to all the others, modeling organizations with strong and centralized leadership.

(f) A random tree network (RTN) to reflect classic hierarchical decision-making systems with non-uniform branching.

(g) A balanced tree network (BTN) modelling a perfectly balanced hierarchy with a branching factor $r = 4$ and a height $h = 4$, creating a symmetrical and regularly stratified organizational structure.

Experiments for each type of network topology were conducted to measure the innovation diffusion process, plotting the evolution in

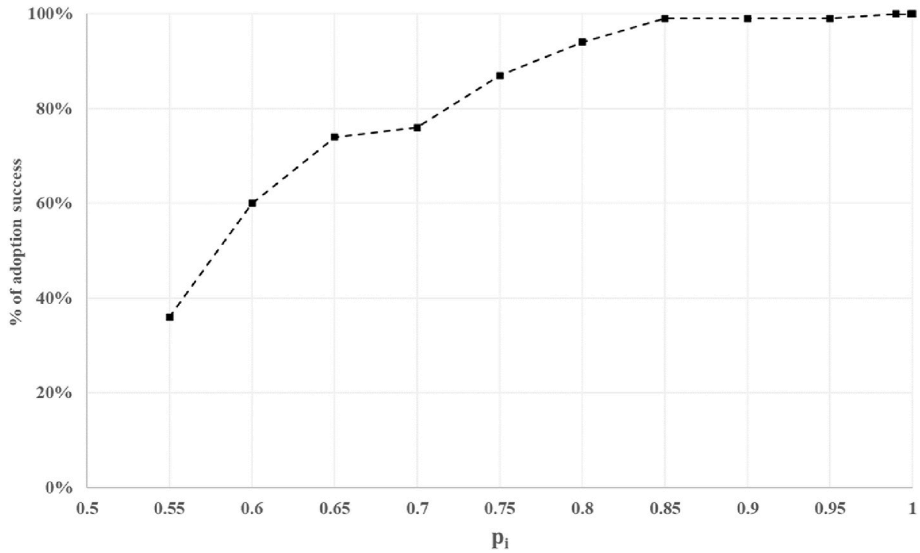


Fig. 8. Percentage of experiments in which the innovation was eventually adopted by all agents (varying p_i).

technology adoption in Fig. 10 to visually appreciate the differences that network structures have in terms of diffusion path variance, diffusion speed, and adoption curve shape. As expected, all topologies present the same final success rate (89 %). Tree-based topologies entail a more linear adoption curve, since the exploration of the number of agents of the network that are stimulated per timestep is bounded by the branching factor of the tree. Another interesting result featured in the experiments is that the more (or better) connected the network is, the faster innovation spreads all over the system, which is the case of complete or random networks (with many connections per agent). However, in less connected networks this could also happen if they allow for fast communication, like in the BAN or NWSN topologies.

It seems clear that the network topology underlying the system influences the technology diffusion process. Fig. 11 presents average results for experiments carried out for different network topologies. It can be observed how CN and RN, i.e. connected networks and networks with multiple connections per agent, outperform other topologies. However, small-world topologies and power-law distributed networks (NWSN and BAN) demonstrate that a small average shortest path length among agents ensures a quick diffusion process. Thus, it is not necessary to have a connected system to spread the technology efficiently (in the same period of time). Another interesting result extracted from the experiments is that tree-like organizations like SN, RTN and BTN are slower in adopting new technology since the communication structure does not allow an agile diffusion.

Although the speed of the innovation diffusion may vary depending on the network topology of the system, the percentage of the adoption success (rate of experimental runs in which all agents eventually adopt the innovation) remains constant. That guarantees that the structure of the network the system relies on affects only the speed of adoption but not the eventual success of the diffusion process.

6.3. Population analysis

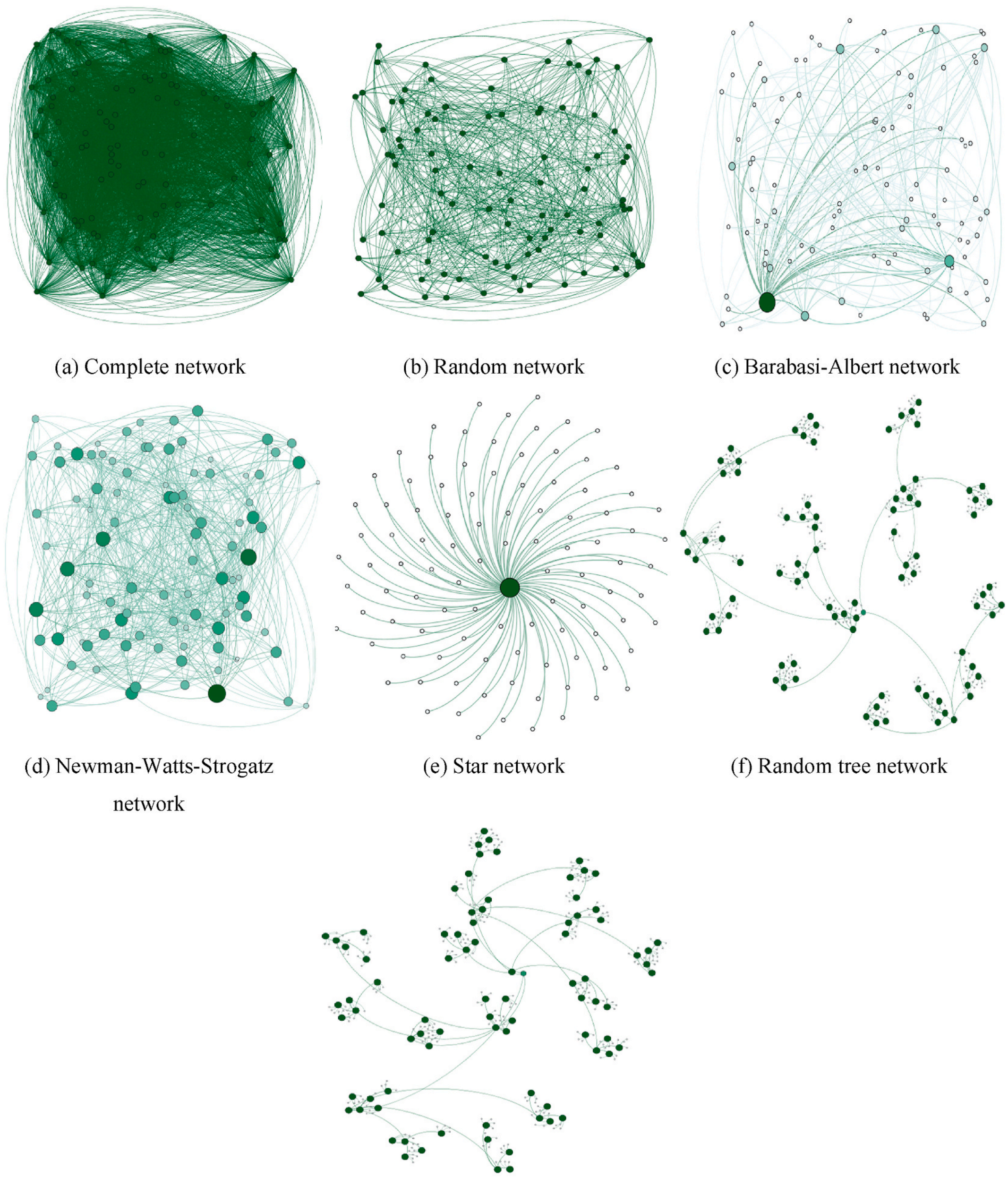
These experiments studied the effect of the number of agents in the system's population. The same parameter setting of network topology experiments are used for a complete network, but the number of agents is now varied using the set of values $\{25, 50, 100, 200, 500, 1000\}$. The obtained results are shown in Fig. 12. It is remarkable that increasing the size of the population of the system does not significantly increase the speed in the technology adoption process. It can be concluded that the number of agents is not a key factor to consider when studying technology diffusion, which means that the change process of a given current technology in an organization behaves the same (in terms of speed) regardless of the size of the system. Furthermore, the rate of adoption success also remains constant regardless of the number of agents in the system. Thus, it is fair to conclude based on these results that the diffusion process remains constant even if the system scales. A comparison of the average results for the simulations with different population sizes is shown in Fig. 13.

7. Conclusions

This article proposes the ASPID model, which represents a significant advance in the understanding and management of innovation diffusion processes with implications for public sector planning. Unlike traditional models, which implicitly assume innovation success and are limited to ex-post analysis, the ASPID model allows us to anticipate both the probability of successful adoption and the risk of failure, crucial information for public policy decision-making. The ASPID model is extraordinarily simple and demonstrates great versatility and generality. Its construction is based solely on agents' decision-making with IBR, and its results are consistent with those of benchmark models in the literature.

One of the most important theoretical advances of ASPID compared to classical diffusion models (Bass, Fisher and Pry) resides in its modeling of innovation failure as an endogenous outcome of the system rather than an exogenous anomaly. Diffusion is conceptualized as a fallible and risk-laden process, not as a gradual accumulation of adopters in a process of unquestionable acceptance. Innovation failure is incorporated into the structure of agents' decisions and network influence, rather than being seen as a rare deviation from a successful process. In the ASPID model, agents can decide to switch from the new technology to the old status quo and vice versa. This is possible thanks to the distinction between stimulus and decision, which represents a novel aspect of diffusion models.

Failure is not understood as the "non-adoption" of innovation, since the performance of innovations is sometimes evaluated excessively optimistically. In this case, resistance to change acts as a natural protection against innovations that would imply reductions in performance [5]. The new approach presents failure as the sum of commission and omission errors, rather than a lack of adoption. Omission errors represent lost opportunities and significant opportunity costs for society. Commission errors occur when the social system adopts an innovation that performs worse than the status quo. These errors generate real costs and efficiency losses. Poorly designed public policies leading to massive



(a) Complete network (b) Random network (c) Barabasi-Albert network

(d) Newman-Watts-Strogatz network (e) Star network (f) Random tree network

(g) Balanced-tree network

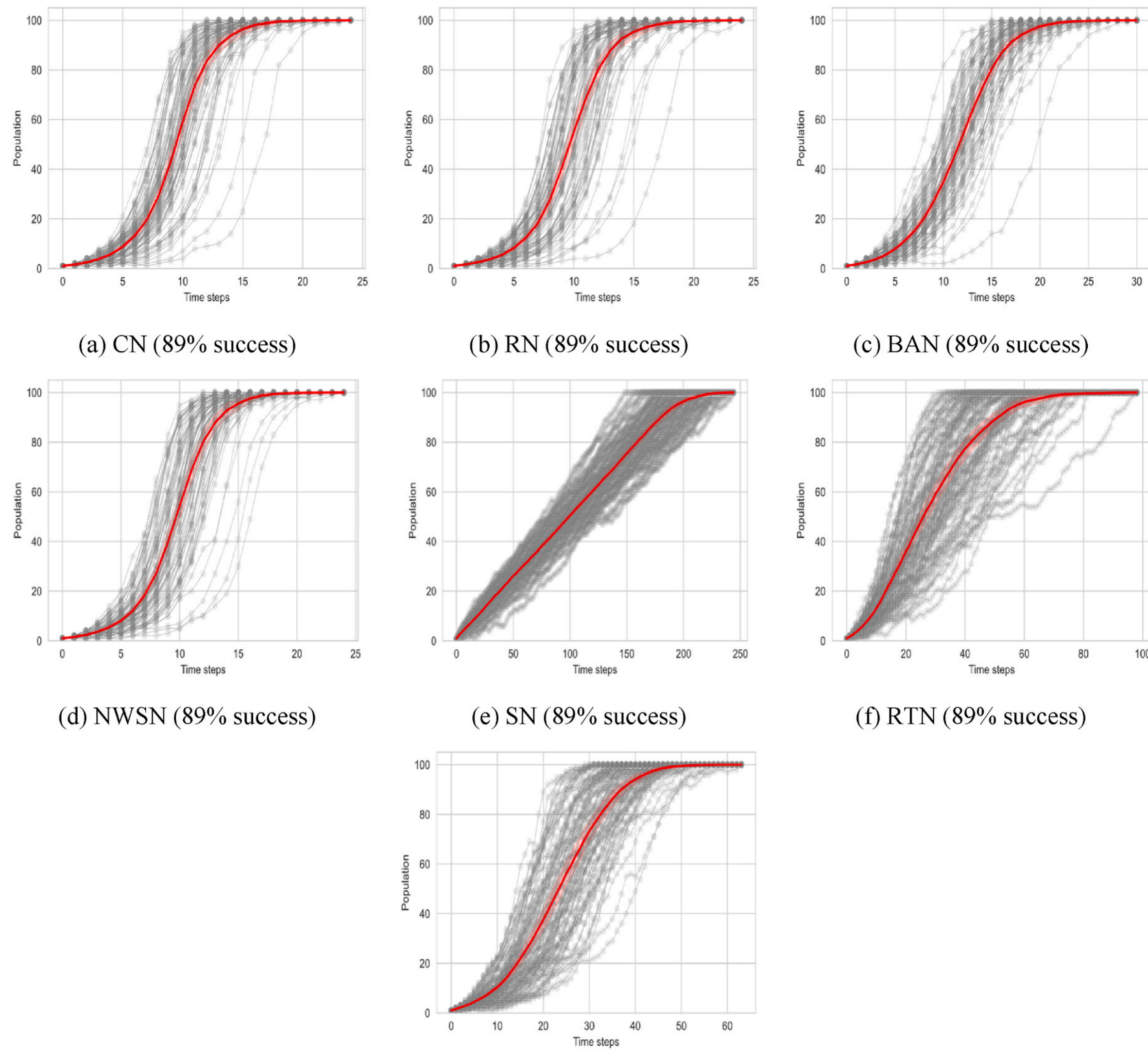
Fig. 9. Different generated network topologies.

investments in suboptimal technologies with significant opportunity costs have been documented [89]. The ASPID model allows public planners to identify structural conditions (network topologies, distribution of expertise) and critical perception thresholds (p_i values) to assess how different policy combinations can inadvertently increase the likelihood of these errors, especially when mechanisms such as social contagion or initial biases dominate over rational performance assessment. This proposal has important implications for diffusion theory, especially those related to failure rates in clean technologies, public health innovations, or digital platforms.

The ASPID model offers greater flexibility than traditional models. It can accommodate any level of information, from aggregated data to detailed individual-level data. This makes it suitable in a wide range of contexts, from aggregated strategic decisions to individual-level adoption decisions. Traditional innovation diffusion models focus on social imitation processes that require historical data for estimation and provide only ex-post information. The ASPID model provides greater depth of ex-post analysis by separating the stimulus (informing the agent that they can change) from the decision itself, where individual and social aspects play a role.

Based on the quality of the innovation, the topology of the target market's interpersonal influence network, and the preferences, beliefs, and experience of the target agents, the ASPID model provides ex-ante predictions of diffusion processes, providing information on the average trajectory and its dispersion relative to it. This approach builds a more realistic probabilistic theoretical framework than that provided by traditional models (which assume that innovation must prevail over the status quo) and provides estimates of the probability of innovation success. This allows public or private managers to make more informed decisions about which innovations are likely to succeed in different contexts and to assess the potential risks associated with innovation diffusion processes.

The ASPID model has been compared with the two most widely used models in the field of innovation diffusion, the Bass model and the



(a) CN (89% success)

(b) RN (89% success)

(c) BAN (89% success)

(d) NWSN (89% success)

(e) SN (89% success)

(f) RTN (89% success)

(g) BTN (89% success)

Fig. 10. Innovation diffusion varying the network topology.

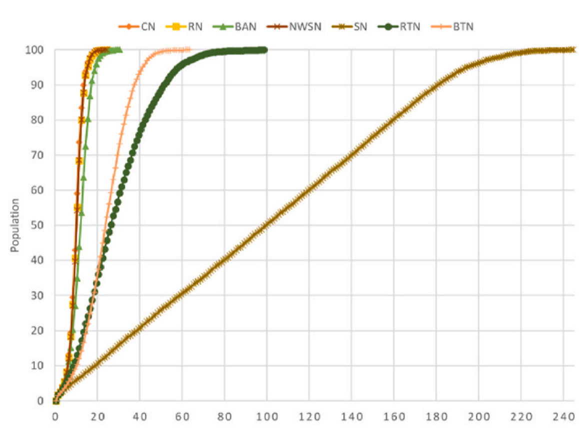
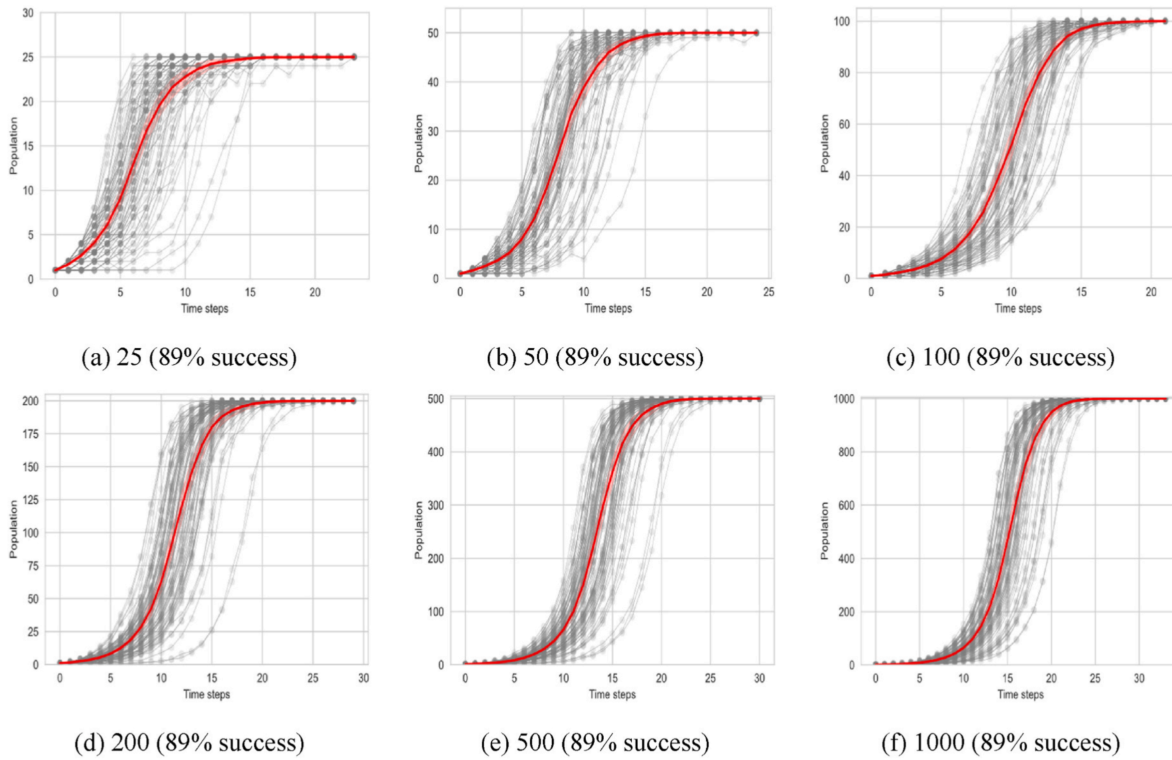


Fig. 11. Innovation diffusion comparison with different network topologies.

Fisher-Pry model. An analysis of the Bass model details some assumptions not previously discussed in the literature and shows that it can be considered a specific case of the ASPID model. The ex-post analysis of diffusion processes shows that the ASPID model can reproduce the trajectories provided by Bass and Fisher-Pry models. Furthermore, it helps elucidate the characteristics of successful innovations. The ex-ante analysis assesses how the quality of the innovation affects the probability of individual adoption, which in turn affects the probability of success, the time required, and the dispersion of the diffusion process, providing insight into how subsidies affect the prices of innovations.

The results reported show that concavity and dispersion of trajectories depend negatively on the latent return difference between the status quo and the innovation. When the gain offered by the innovation over the status quo is small, it generates hesitation among individual agents, slowing diffusion and increasing the variance of the diffusion process. Network topology also affects the diffusion process (time required, variance, and shape). Tree-based topologies have more linear shapes than other topologies. Topologies with more average connections per agent are faster, highlighting that small-world (NWSN) and power-law (BAN) topologies are particularly efficient (requiring fewer connections to achieve the same speed), while tree topologies are the least efficient. Another consistent result is that when there is no social influence on decisions, the adoption success rate does not depend on the network topology. Finally, the results showed that system size (number of agents) is not a key factor modifying the characteristics of the



(a) 25 (89% success) (b) 50 (89% success) (c) 100 (89% success)

(d) 200 (89% success) (e) 500 (89% success) (f) 1000 (89% success)

Fig. 12. Innovation diffusion varying the population size.

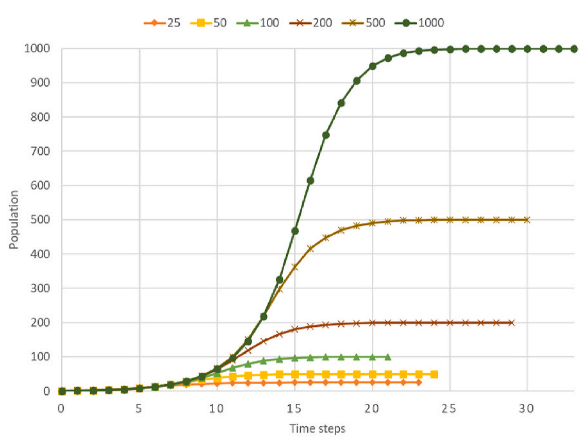


Fig. 13. Innovation diffusion comparison with different population sizes.

diffusion process.

Overall, the analyses presented in the paper can serve as a guide on how the ASPID model can be used to provide valuable information about the innovation diffusion process. The model's ability to provide ex ante information on the probability of success of innovations is particularly valuable for public innovation management, as it allows for planning operations related to innovation diffusion processes and assessing potential risks associated with them, facilitating.

- *The optimization of intervention strategies.* The results demonstrate that small increases in the individual probability of adoption (p_i) generate large increases in the overall probability of success. This suggests that public planners should concentrate initial resources on disseminating information about the innovation's benefits or providing direct support that modifies its value, rather than trying to convert staunch opponents or reinforce convinced adopters.
- *Adaptive management of public policy.* The variance in diffusion trajectories reveals the need to design adaptive public policies with early monitoring mechanisms. Reported simulations showed that above-average adoption behavior tends to be moderate but frequent, while below-average behavior can be much more extreme but less likely. This suggests the need for robust contingency plans for infrequent but possible pessimistic scenarios. In general, the analyses presented can serve as a guide to 'how the ASPID model can be used to provide valuable information about the innovation diffusion process'. The model's ability to provide ex-ante information about the probability of success of innovations is particularly valuable for management, as it allows managers to plan operations related to innovation diffusion processes and assess potential risks associated with them.

The versatility and flexibility of the model can make it suitable for use in a wide range of contexts and fields of knowledge. Some future avenues of the model are.

i) Restating the model in a dynamic way (p_i^t) could allow analyzing the dissemination of knowledge in a social system, distinguishing between the incorporation of information and the evolution of prejudice in a Bayesian way (p_i^{t-1}) up to the improvement of expertise by modifying the beta parameter;
ii) Alternative stimulus systems to word of mouth can be incorporated, incorporating unidirectional networks such as advertising in the media or the like;
iii) The idiosyncrasies of the agents can be incorporated, making the latent returns of the status quo and innovation different for each one of them ($V_c^i; V_s^i$);
iv) Allow the incorporation of learning by use, through the increasing of the latent performance of the chosen alternative. Therefore, the development of models of diffusion of knowledge or diffusion of ideas seems to be a promising line of future research.

CRediT authorship contribution statement

Carlos Sáenz-Royo: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Ramón Hermoso:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Francisco Chiclana:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization.

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Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Carlos Saenz-Royo reports article publishing charges and equipment, drugs, or supplies were provided by Spanish Ministerio de Economía y Competitividad. Carlos Saenz-Royo reports article publishing charges and equipment, drugs, or supplies were provided by Diputación General de Aragón. Carlos Saenz-Royo reports article publishing charges and equipment, drugs, or supplies were provided by Spanish State Research Agency. Carlos Saenz-Royo reports article publishing charges and equipment, drugs, or supplies were provided by UNIZAR-Comuniter. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

No data was used for the research described in the article.

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