Technovation 124 (2023) 102741

Contents lists available at ScienceDirect

Technovation

journal homepage: www.elsevier.com/locate/technovation

Authoritarianism versus participation in innovation decisions

Carlos Sáenz-Royo [a,*], Álvaro Lozano-Rojo [b]

[a] University of Zaragoza, Spain
[b] IUMA - University of Zaragoza, Spain

ARTICLE INFO

Handling Editor: Dr Stelvia Matos

Keywords:
Participatory decision
Resistance to innovation
Social influence
Adoption process
Commission error
Omission error

ABSTRACT

Why do innovation projects fail? The most common answers are (A) the implementation differs from what was planned; (B) despite positive expected payoffs, there is an ex-ante positive probability that payoff can be negative (risk). As a third option, we consider the fallibility of individuals who evaluate innovation projects using their limited information-processing capabilities (bounded rationality). Furthermore, we compare the overall organizational performance of two decision mechanisms. First, an informal *Collective Decision* as an unanimity participative mechanism to decide on technological innovation adoption and, second, a centralized *Authority* decision. *Authority*-based decision-making results in higher commission errors (acceptance of projects that an unbounded rational decision-maker would reject) and lower omission errors (rejection of projects that an unbounded rational decision-maker would accept) than *Collective Decision*. In a dynamic technological adoption process where a sequence of randomly generated innovation projects is evaluated using the two mechanisms, the simulations show that, in the short-term, omission errors dominate and *Authority* is preferred to *Collective Decision*; however, in the mid and long terms, commission errors dominate and *Collective Decision* is preferred to *Authority*, especially if *Collective Decision* does not incorporate social influence. With *Collective Decision*, the ratio of projects that fail is lower, more innovation projects are rejected, and fewer innovation projects are accepted, which can be interpreted as resistance to innovation.

1. Introduction

The prevention of failure of innovation projects is a justified concern of innovation management (Jarrel, 2017; Meaney and Pung, 2008; Porras and Robertson, 1992). There are two main explanations of why innovation projects do not deliver the promised results. One of them attributes failure to errors or lack of commitment in the implementation stage (Dent and Goldberg, 1999; Dubrin and Ireland, 1993; Furst and Cable, 2008; Griffin, 1993; Hardy and Clegg, 2004). This may be because those involved in the implementation stage did not participate in the decision-making process or because they resist change and innovation (Dam et al., 2008; Kotter and Schlesinger, 1989; Piderit, 2000). The other explanation recognizes that innovation decisions are risky, and payoffs depend on states of nature (related to the technology and/or demand) that are uncertain during decision-making (Rogers, 1962; Schumpeter, 1934; Wang et al., 2010).

We propose a third explanation for failure based on the limited rationality of the individuals involved in the decision, that is, individuals often make errors in their judgments because of the brain's limitations in information-processing (Simon, 1947). In rationality, the amount of available information is exogenous for individuals and determines (inversely) the uncertainty, consequently affecting the risk associated with the alternatives. Nevertheless, in limited rationality, all the information is available. However, using the same information, one individual can reach a different decision than another because the two may have different capacities for processing the information. In this conceptual framework, the decision stage is crucial because the performance solely depends on individuals' ability to predict and the group decision mechanisms that combine their abilities to reduce errors. Decision mechanisms are deeply analyzed when results are poor (Du et al., 2007; Wang et al., 2010; Wang et al., 2010), which is a topic deserves more research attention according to some authors (Frishammar et al., 2012; Huang et al., 2013).

This article uses the Agents-Based Modeling (ABM) simulation methodology (Fioretti, 2013; Macy and Willer, 2002) to compare the performance of two mechanisms to take decisions on innovation projects as development opportunities in organizations. One of these mechanisms centralizes the information and decision to accept or reject

* Corresponding author.
E-mail addresses: csaenz@unizar.es (C. Sáenz-Royo), alozano@unizar.es (Á. Lozano-Rojo).

https://doi.org/10.1016/j.technovation.2023.102741
Received 28 August 2020; Received in revised form 26 January 2023; Accepted 28 February 2023
Available online 14 March 2023

innovation projects. This process is conducted by a single individual in the hierarchy of the organization (*Authority*). The other mechanism requires consensus among the members of the organization arranged in a network. The undirected succession of interactions between directly connected individuals can end with a consensus on adoption or rejection (*Collective Decision*).

Given that individuals can make two types of errors in their judgments, namely, commission errors (supported projects that should be rejected) and omission errors (rejected projects that should be accepted), determining the decision mechanism is crucial. Under *Authority*, the bounded rationality of the individual with the decision-making power affects the probability of committing any of these errors. However, under *Collective Decision*, the probability of omission and commission errors is determined on a case-by-case basis depending on the random interactions among individuals. Here, decision-making individuals are also involved in the implementation stage, unlike in the *Centralized Authority*.

Our model assumes that innovation projects can show higher or lower performance than the status quo and the decision mechanisms affect the types of errors appearing in the final payment. This approach allows the analysis of the aspects that have not been previously discussed in the literature, such as the fact that the *Collective Decision* reduces commission errors but increases omission errors when compared with *Authority*. From a more practical point of view, this suggests that, under *Collective Decision*, the number of accepted projects will be fewer; however, the number of failed projects will be lower than under *Authority*. Therefore, *Collective Decision* can be seen as a mechanism that creates resistance to innovation in organizations (Lewin, 1947). Whether resistance to innovation is positive or negative for organizational performance, is hard to tell. It might be positive for organizational performance when avoiding mistakes is a priority (some decisions may threaten the survival of the organization), but its potential benefits must be weighed against the opportunity costs of omission errors. Here, we link opportunity costs to too much resistance to innovation under *Collective Decision* mechanism. The effect of the two error types on performance is not clear, which is a question that the simulation helps answer. Outside and inside observers of innovation success and failure find it difficult to assess the opportunity costs of omission errors when evaluating the performance of innovation projects. The simulation methodology allows us to explicitly introduce the consequences of omission errors in the evaluation of the performance of the elements that influence innovation decision-making.

Another innovative aspect of our study is that we examine the decision mechanisms sensitivity to the density and centrality of social ties when they become social influences. In the decision-making context, this indicates that individual support for the adoption of an innovation project depends on the outcome of project-related information-processing and number of supporting neighbors. We find that social influence increases the “resistance to innovation” (Lewin, 1947). The relevance of the centrality and density of social ties has also been examined in joint production situations where individual contributions to group production are affected by incentives to free ride (Marwell et al., 1988; Oliver et al., 1985). The difference is that the potential inefficiencies in the proposed modeled situation arise from individuals’ fallibility and intention to be collectively rational (all members of the organization work as a team and share the organization’s common goal of maximizing the expected payoff to the group, there are no conflicts of interest and no incentives to lie while sharing information with other members of the group).

The remainder of this paper is organized as follows. Section 2 reviews the literature on the conceptual framework of our model. Section 3 describes the formal model development and Section 4 presents the simulation results for *Collective Decision* versus *Authority*. Finally, Section 5 discusses the results, proposes future research directions, and summarizes the most relevant conclusions.

2. Literature review on the modeling framework

A large body of literature has examined the failure of innovation projects in the context of the resistance to innovation, which occurs in the implementation stage (Furst and Cable, 2008; Hardy and Clegg, 2004). However, many authors have demanded mode research on the innovation-decision stage and its impact on the performance of the adoption process. Wang et al. (2010) have pointed out that many studies are based on post-determination models and emphasize the lack of studies on decision rules. Huang et al. (2013) have stated that “The use of decision analysis approach to quantitatively deal with the technology adoption decision problem has not often been seen in the literature.” Du et al. (2007) have pointed out that “Despite the substantial body of research on the determinants and effects of innovation, surprisingly little is known about the decision-making process of the innovation-decision.” This claim has been highlighted in Frishammar et al. (2012), which contains a literature review on why innovation projects fail. Its conclusion states that “… a key issue in both strategic management and entrepreneurship, the distinct skills, procedures, and decision rules, which underlie firm-level sensing in process innovation, remain largely unexplored. Accordingly, we encourage further research into process innovation, which may well arrive at conclusions that are equally relevant to academics and practitioners in light of an increasing interest in the determinants of successful process innovation.”

Other researchers have criticized the deterministic and static approaches adopted by studies on innovation projects failure (Hobday, 2005), even when organizations are in a changing environment where new technologies constantly appear, generating innovation projects. Wang et al. (2008) have expressed the need for literature that explores the dynamic nature of innovations and technological change.

Our study tries to reduce these research gaps by evaluating how hidden decision mechanisms and organizational elements influence the performance of an organization in a dynamic adoption process where the organization must decide on a sequence of innovation projects whose performance cannot be accurately anticipated by individuals (bounded rationality) in an unlimited time horizon. Although the selection of innovation projects is a fundamental part of the innovation process, the results of the decision mechanisms by which organizations evaluate innovations remain unexplored. This research gap exists because researchers cannot evaluate the omission errors of innovation projects, and some of the decision processes may be unobservable (like social influence).

To alleviate these problems, we use the ABM as a laboratory (controlled environment) in which a scenario (decision mechanism and organizational elements) is evaluated using simulated performance (Kuandykov and Sokolov, 2010; Sharma and Sehrawat, 2021). The inputs to the simulation are the number of individuals in the network, ties of each individual, degree of fallibility of individual members, and assumptions about social influences. We use ABM to study how individuals in an organization can indirectly influence the collective decision on whether an innovation project will perform better than the current status quo or not.

2.1. Decision mechanisms

Despite the difficulties in studying decision mechanisms, some empirical studies have found positive relationships between the success of innovations and degree of participation in decisions (Cohn, 1981; Kim, 1980; Russell and Russell, 1992). These studies have conjectured that decision mechanisms that involve all individuals overcome the drawbacks of the traditional concentration of decisions for two reasons. First, collective decision mechanism allows the collection of a greater amount of information and second, the commitment gained in the decision stage simplifies the implementation stage. However, some works have found that authority promotes the adoption of disruptive innovations that pose significant challenges and are not assumed by other forms of decision-making (Lee and Csaszar, 2020; Seshadri and Shapira, 2003).

The hierarchical structure has concentrated decision-making power in the hands of a few individuals, giving them the capability to accept or reject innovation (Sah and Stiglitz, 1986) (*Authority*). However, participation systems are gaining prominence (Raab and Kenis, 2009). To maximize participation, *Collective Decision* is conceived as a discussion forum where nothing is imposed, and all members are treated equal (unanimity). Here, we evaluate the following two decision mechanisms: *Authority* being the traditional one and *Collective Decision* being the participatory system. Accordingly, we provide explanations for the ambiguities found in empirical intuitions.

2.2. Organizational elements

Organizational innovation decisions are rarely probabilistically studied and how some internal determinants affect the probability of adopting an innovation is even more underexplored (Du et al., 2007). When individuals participate in decision-making, they are aware of others' actions and their social ties enable social influence (Marwell et al., 1988). Group decision models should account for these interdependencies in the manifestation of individual judgments of collective action (Hardin, 1982; Oliver et al., 1985) because social ties allow the transmission and discussion of information. Even so, they have been widely ignored in the group decision literature (Christensen and Knudsen, 2010, 2002; Csaszar, 2013; Knudsen and Levinthal, 2007; Sah and Stiglitz, 1986). Social ties may result from formal relationships (communication channels consciously established by the organization) or informal relationships (individually chosen social ties) and affect interdependent decisions. Two important organizational characteristics of social ties are centrality and density and, ceteris paribus, the changes in them substantially alter group outcomes (Marwell et al., 1988).

2.2.1. Individual judgment

Most literature on reliability of organizational decision-making mechanisms (Christensen and Knudsen, 2010, 2002; Csaszar, 2013; Knudsen and Levinthal, 2007; Sah and Stiglitz, 1986) has assumed that everyone is a potential pioneer; if they receive information of an innovation project, they submit it to the organization to decide whether to accept or reject it, hoping to improve their collective performance. Hence, we assume that individuals have no strategic behavior, and the exchange of information and manifestation of judgments are cost-free. The anticipation of the performance of an innovation project depends on the judgment capacity of the organization, which contrasts with the literature influenced by Schumpeter (1934), where success or failure of the innovation occurs randomly. Group fallibility is analyzed in a bounded rationality framework where the information is complete. The uncertainty in the result is the product of the limited capacity for individual judgment, which is alleviated by group decision mechanisms.

In this area, the models of individual judgment are straightforward. In the model of Du et al. (2007), the probability of showing a correct judgment is described using the normal distribution of an individual's error, independent of the difficulty of the decision. Knudsen and Levinthal (2007) have proposed a linear function where the individual error probability is proportional to the performance difference between the status quo and new project. Luce (1956) has used logit distribution, which is more flexible, and combined the previous two methods. It allows different individual's information-processing abilities and the probability of correct judgment increases with the performance difference between alternatives (Sáenz-Royo et al., 2022). This probability captures the behavior of individuals with bounded rationality, following Simon (1947). This model of individual behavior has been widely used across decision-making studies (Pachur et al., 2017; Salas-Fumás et al., 2016; Scheibehenne and Pachur, 2015; Sutton and Barto, 1998). Additionally, Salas-Fumás et al. (2016) have argued that social environment influences the probability of an individual accepting an innovation project, connecting social interdependencies and individual judgment.

2.2.2. Centrality

The concept of centrality tries to collect asymmetries in the importance level of some individuals, compared with others in a network of social ties (Borgatti and Everett, 2006; Freeman et al., 1991; Wasserman and Faust, 2013). Individuals with high centrality have more social ties and can send and receive more information than others. If all individuals are connected to only one other individual and there is no connection among them, the structure has maximal centrality (Wasserman and Faust, 2013). However, if all individuals have the same number of ties, their centrality is minimal (Freeman, 1978; Marwell et al., 1988).

For efficiency, in an authoritarian decision mechanism, the authority must have maximal centrality because any relevant information should reach her as soon as possible. In this decision mechanism, each proposal must convince only the authority; hence, the determining factor is authority's bounded rationality. If this individual is incompetent or incapable, the organization is doomed to fail (Marwell et al., 1988).

However, for a collective decision to be egalitarian, it must show minimal centrality and must pass the judgment of everyone without a fixed itinerary. After the dissemination process,[1] unanimity is achieved in favor of the innovation project or status quo, with all members decisively participating in the group decision (Farjoun, 2010; Tsoukas and Chia, 2002). Unanimity forces equality among all individuals and empowers them as essential in the organization by involving everyone in the discussion and imposing no conditions. Accordingly, unanimity ensures that everyone is committed to the decision. However, any majority mechanism generates the following two groups of individuals: those who impose and those who must accept. From a normative perspective, unanimity is better at maximizing well-being than a benevolent dictator (Buchanan et al., 1962; Romme, 2004). With three or more alternatives, unanimity is free from the inconsistency of a majority rule voting system (Arrow, 1963). At the organizational level, unanimity enables coordination and cooperation among everyone in the implementation stage (Kellermanns et al., 2011 and the references therein). Group unanimity is also recommended when incorrect decisions could severely damage the group (Catalani and Clerico, 1996).

2.2.3. Density

The maximum centrality of authority forces the number of ties per individual to be asymmetric and fixed, number of social ties of the deciding individual is $N-1$, where N is the size of the organization, and the others have only one social tie. However, minimum centrality is achieved if the number of social ties of individuals is equal. In this case, when the group size is fixed, the number of ties is equivalent to the density of the social network (the number of ties over the total number of possible ties). The larger the number of social ties, the faster the dissemination (Marwell et al., 1988). But social ties can generate social influence on the judgment of individuals that do not have obvious effects on the process. Oliver et al. (1985) have argued that judgments are not simultaneously established but sequentially appear, which justifies the study of social influence. Granovetter (1978), Cialdini and Goldstein (2004), and Salganik et al. (2006) have described that "social influence" as the weight of environmental judgment on one's own mind. This means that, in an organization, the probability of an individual being inclined to favor the acceptance of an innovation project increases with the relative number of individuals who have previously opted for this judgment within their social circle. Jones (2003) has argued that

[1] In collective action, the modeling of the dissemination of trials is inspired by epidemiological models for the spread of diseases and pathologies in human groups adapted to the social environment. See, for example, Bass (1969), extensions such as Mahajan et al. (2000), and the later introduction of the model in Complex Networks by Moore and Newman (2000), Newman (2002), and Dodds and Watts (2005).

bounded rationality sensitives individuals to others' judgments because they are unsure of their own. Therefore, the number of social ties in a group of a fixed size—network density—largely influences individual judgments and may affect the performance of collective decisions.

2.3. Resistance to innovation

In a collective decision, organizational elements such as unanimity, social influence, and density are summarized through different levels of resistance to innovation. When the ability to decide is centralized to one person (authority), the elements above do not generate any resistance in the decision process but it can appear in the implementation stage. However, a collective decision involves organizational elements that can lead to resistance to innovation in the decision-making stage, alleviating the uncertainty in the implementation stage.[2] The concept of resistance introduced by Lewin (1947) entails the idea that an equilibrium can retain the status quo, when an organization is facing the forces of change. The term "social dynamics" acknowledges the importance of each individual in the group and their interaction as generating resistance elements (Burnes and Cooke, 2013). When individual judgment is not affected by social influence, the density of social ties does not affect the probability of acceptance of the organization; resistance to innovation comes from the need to convince all individuals (Salas-Fumás et al., 2016).

Resistance to innovation is a result of the dynamics of discussion and social influence, originating from a disagreement regarding the perceived performance of an innovation project. From an organizational perspective, a collective decision can be interpreted as a way of creating "resistance" to innovation that counteracts the possible excess of optimism, which may lead empowered managers accepting too many innovation projects (Ford et al., 2008; Piderit, 2000). Allowing a collective decision shifts the organization into a more cautious position, reducing commission errors but increasing omission errors when compared with authoritative decision-making (Salas-Fumás et al., 2016); hence, it is critical to assess this balance.

2.4. Adoption process

Wang et al. (2008) have expressed the need to understand the dynamic nature of innovations and technological change. In this sense, Ilori and Irefin (1997) have studied technological innovation using decision theory. The adoption process is dynamic because the organization must decide which innovation projects to adopt in an infinite temporal horizon; moreover, each of these innovations has a different performance. In this study, the adoption process is conditioned by previous decisions and the ability to predict the performance of the organization (decision mechanism) (Rogers, 1962). We consider that each innovation project can present a positive or negative performance balance in the status quo. The contributions of innovation include improving productivity (Adler and Clark, 1991; Balasubramanian and Lieberman, 2009; Sáenz-Royo and Salas-Fumás, 2013) and/or reducing costs (Sinclair et al., 2000; Yelle, 1979; Zangwill and Kantor, 1998). The dynamic framework allows the observation of the evolution of the performance across different scenarios (decision mechanism and organizational elements) over time, establishing the intervals in which they perform the best (Farzin et al., 1998). Understanding the adoption of technological innovations over time and how they affect organizational performance is key in management.

[2] Under *Collective Decision*, some cases of irrational immobile behavior have been observed in an attempt to maintain harmony among members. This phenomenon is known as "Groupthink" (Esser, 1998); however, this psychological aspect is not included in our stylized model.

3. Description of the model

The adoption process is modeled as a time series of innovation projects, one project per period. The organization includes N individuals, one in each node of the connected network. At the beginning of each period, the level of collective performance is V^s. The everyday working activity of the group takes place in an environment of technological innovation—in each period, any individual can propose an innovation project that can change the status quo performance; the innovation project is represented by its latent performance and inaccurately predicted by individuals (bounded rationality). The distribution and moments of the random variable $\widetilde{V}$, which generates innovation projects, are known (expected value $E(\widetilde{V}) = \overline{V}$ and standard deviation $SD(\widetilde{V}) = SD$). The group starts with a status quo payoff of V^s. If a new project of value V is accepted, the status quo changes to this value V. The optimal decision to maximize the sum of the values of the successive innovation projects along a sequence of periods, is to only accept projects with payoffs higher than the status quo.

The organization can make decisions using an *Automatic System* or a decision mechanism (*Authority* or *Collective Decision*). The dependent variable in the model is the performance level obtained over time, after each innovation project proposal has been evaluated. The independent variables are the decision mechanism and organizational elements (the existence of social influence and density of social ties). Each combination of independent variables defines a different scenario.

The *Automatic System* is based on the average performance of innovation projects. If the average of the innovation projects is higher than that of the status quo, each innovation project that reaches the organization will be accepted without any additional evaluation.[3] The ex-ante expected performance of the organization will be the expected value of the random variable of project performance, $E(\widetilde{V})$. If the average of the innovation projects is lower than the status quo, the decision is to reject all innovation projects. Furthermore, the performance of the group is that of the initial status quo, V^s.

The decision mechanisms try to anticipate the latent performance of each innovation project (a priori unknown to individuals) and finally decide whether to accept or reject it. The following two decision mechanisms are considered: *Authority* and *Collective Decision*. In both cases, individuals are fallible, which is described later. In the collective decision mechanism, the individual judgment of adoption may or may not be influenced by the judgment of neighboring individuals.

3.1. Decision mechanisms

The acceptance or rejection of each innovation project (against current status quo) is obtained through a simulation, modifying the value of the status quo if it is accepted. Repeating this process with *Collective Decision* and *Authority* we can compare the expected performances of both mechanisms.

Hence, the process begins with one individual in the organization proposing an innovation project whose latent performance is V^c which may be higher or lower than status quo V^s. Thus, we study how an innovation project that unexpectedly appears at any point in the organization is accepted.

3.1.1. Authority model

Under *Authority*, a single individual makes decisions (authority) and other individuals limit themselves to making proposals. All members of the organization are directly connected to the authority and can transmit any improvement proposals (maximum centrality). Power is asymmetric and there is no social influence or resistance in the decision-making process. In this case, each project must overcome the skepticism of the

[3] Even if the performance is inferior to the average in a given period.

bounded rationality of the authority, whose probability of acceptance is

$$p_A = \left(\frac{e^{V^s}}{e^{V^c}} + 1\right)^{-1}. \quad (1)$$

This probability exclusively depends on the comparative advantage/disadvantage performance of the innovation project, as compared to that of the status quo (V^s/V^c). For each project, only one change in judgment is possible. This is because if the authority favors the adoption of the innovation project, it will be implemented in the organization; if it favors the status quo, the innovation project will be rejected.

3.1.2. Collective decision model

In *Collective Decision*, the innovation project must iteratively overcome the skepticism of all recipients of the innovation, without a fixed itinerary. This is because, initially, all individuals favor the status quo. At the end of the dissemination process, unanimity is reached in favor of the innovation project or status quo.

For any individual a, two possible judgment states are defined in each iteration i, namely, $a_{s,i}$, which supports the status quo, or $a_{c,i}$, which supports the innovation project. Interactions occur only among individuals with different judgments. Suppose that in iteration i, b is an individual who has a favorable judgement for innovation project ($b_{c,i}$). Next, we choose another individual a who favors the status quo ($a_{s,i}$) within b-environment. Then a interacts with b. After each interaction, the following two cases are possible: the individual favoring the status quo (a) is convinced by the innovation project (transition probability $p^c_{a,i}$) or the individual favoring the innovation project (b) is convinced of the status quo (transition probability $p^s_{b,i} = 1 - p^c_{a,i}$). The transition probabilities ($p^c_{a,i}$; $1 - p^c_{a,i}$) depend on the relative weight of innovation performance concerning the status quo. For an independent individual, a (not influenced by others), the probability of changing their judgment and accepting the proposal at iteration i is

$$p^c_{a,i} = \left(\frac{e^{V^s}}{e^{V^c}} + 1\right)^{-1}. \quad (2)$$

However, under free participation, social environment judgments are likely to influence individual judgments, modifying the probabilities of transition (social influence). In this case, the transition probability $p^c_{a,i}$ is defined as

$$p^c_{a,i} = \left(\frac{na_{s,i}e^{V^s}}{nb_{c,i}e^{V^c}} + 1\right)^{-1}, \quad (3)$$

where $na_{s,i}$ is the number of individuals in the a-environment (including a) who present the same judgment (favorable to the status quo). Similarly, $nb_{c,i}$ is the number of individuals in b-environment (including himself) who also favor the project.

The probability combines two factors that determine the acceptance of the innovation project, latent performance of the innovation project in relation to the status quo, e^{V^s}/e^{V^c}, and relationship between the number of individuals in a-environment who favor the status quo, and those in b-environment who favor innovation ($na_{s,i}/nb_{c,i}$), in iteration i. Notably, equation (2) is a particular case of equation (3) when $na_{s,i}$ and $nb_{c,i}$ are equal to 1—when individuals consider their judgment without social influence.

The greater the relative improvement in the innovation project and greater the number of individuals favoring the innovation project (and fewer against it), the greater the probability that each interaction will end with an individual favoring the innovation project. Similarly, the probability of an individual favoring the innovation project modifies their judgment in favor of the status quo is

$$p^s_{b,i} = \left(\frac{nb_{c,i}e^{V^c}}{na_{s,i}e^{V^s}} + 1\right)^{-1} = 1 - \left(\frac{na_{s,i}e^{V^s}}{nb_{c,i}e^{V^c}} + 1\right)^{-1} = 1 - p^c_{a,i}. \quad (4)$$

Social influence depends on social ties. When individuals are highly connected (high density), they exercise greater influence on the environment; when individuals are more isolated (low density), their judgment that depends on the quotient between the exponential relative values (e^{V^s}/e^{V^c}) to a greater extent.

3.2. Scenarios

A scenario is a combination of decision mechanism and organizational elements that modify the probability of accepting innovation projects. Six scenarios are defined. The acceptance probability of an organization is denoted as $p(e^{V^s}/e^{V^c}|k)$, where k is the scenario.

3.2.1. Automatic System scenario (Scenario S)

Given that the organization knows the average performance of innovation projects, it can establish an a priori automatic decision. If this average is higher than that of the status quo, all innovation projects are accepted without any further evaluation; if it is lower, all are rejected. Notably, the decision is not made based on a project's (unknown) performance but on the global average. This automatic decision mechanism is known as the expected value criterion. This scenario is used as the "reference case."

3.2.2. Authority decision mechanism (Scenario A)

Under *Authority* decision mechanism the authority studies each project. The probability that the authority accepts each innovation project equation (1) is calculated similarly as the interaction in *Collective Decision* without social influence equation (2). This is because the authority is not influenced by organizational elements.

3.2.3. Collective decision mechanism (Scenario C)

During the decision process for each innovation project, the opposing forces summarized in the individual probabilities defined in equation (3) and equation (4), are at play. This process is simulated using an ABM (see Appendix I). The result shows the group decision of a given simulation, relative performance between the innovation project and status quo, existence or absence of social influence in individual judgments, and density of social ties in the case of social influence.

3.2.4. Collective decision without social influence (Scenario C1)

When an individual is not influenced by their environment, $na_{s,i}$ and $nb_{c,i}$ are equal to one, and neither the place where the innovation project appears nor the density of social ties affects the group probability. Therefore, group resistance to an innovation project results from having to convince all members, where the probability of individual judgment only depends on the relative performance of the innovation project when compared with the status quo. In this case, the maximum density social ties are considered because they allow the fastest diffusion (minimum iterations).

3.2.5. Collective decision with social influence (Scenario C2)

The following three levels of density of social ties are considered for a group of 13 individuals:

- *Low Density Network (Scenario C2-1)*: two ties per individual being the lowest possible density
- *Medium Density Network (Scenario C2-2)*: six ties per individual, a medium density within the possible ones
- *High Density Network (Scenario C2-3)*: twelve ties per individual, the maximum density

3.3. Adoption process

An organization size of $N = 13$ individuals was selected for two reasons. First, a collective group decision has special relevance in small- and medium-sized groups. Second, one of the robustness exercises verified that the variations in the group probabilities are low for an organization whose size greater[4] than 13. Moreover, in the authoritarian case, organization size is not relevant because of the centralization of decisions in the node with the authority.

The simulation aims to compare the performance of the organization in the designed scenarios. The simulation starts with the status quo of a group. Its economic value is normalized to $V_0^s = 1$. Innovation project shocks are represented by the realizations of a random variable that is the economic value of technological change, $\widetilde{V}^c$. For simulation purposes, the innovation project values are 1000 random draws from a normal distribution with an expected value of 1.2 and standard deviation of 0.2: $\widetilde{V}^c \sim N(1.2; 0.2)$. The innovation projects appear sequentially, one in each period. The sequence is the same across all scenarios. The underlying technology offers an average performance that is 20% higher than that of the initial status quo. However, in the scenario where all projects are accepted (*S*), there is a probability of 0.1587 that an innovation project with a performance lower than 1 (initial status quo) would be accepted.

The performance of the scenarios is obtained through the simulation. The probability of accepting an innovation project always depends on the performance difference (between the status quo and latent performance of the innovation project) and characteristics of each scenario, $p(e^{V^s}/e^{V^c}|k)$. According to this probability, the simulation produces a random walk of performances (one for each period), which is obtained in a specific scenario (we will denote it as SV_t^k) with a standard deviation (we denote it as SD_t^k). We define the average cumulative return up to period *t* as the sum of the returns obtained up to that period, divided by the number of periods (we denote it as CSV_t^k). The number of cumulative "changes" is defined as the number of innovation projects accepted up to period *t*. This concept is important because every time an organization accepts an innovation project, the organization must transform itself; we call this process "change" and it involves obtaining a new performance (SNA_t^k). For the sake of replicability, Appendix II provides the detailed simulation procedure and interpretation of the technical part.

4. Performance of the scenarios

We simulated the performance of each scenario *S*, *A*, *C*1, *C*2-1, *C*2-2, and *C*2-3 for a sequence of 1000 innovation projects. The performance evolution of the different scenarios allows the comparison between the decision mechanisms and organizational elements that define each scenario in the short and long terms. Table 1 and Fig. 1 show the scenario performance across different periods, standard deviation, and visualization of their different adoption processes.

Table 1 shows how, in period 100, Scenario *A* presents a result of 1.11. The performances are 1.49, 1.46, 1.19, and 1.02 for Scenarios C1, C2-1, C2-2, and C2-3, respectively. As mentioned before, in decision mechanism (scenarios *A* and *C*), the scenario performance in each period depends on the acceptance (changes) and rejection decisions from the previous period. The maximum variability of expected performance (difference between adjacent periods) is presented by *Automatic System*, followed by the *Authority*. The *Collective Decision* scenarios show less variability despite the different trends. Notably, Scenarios *S* and *A* show rapid growth in performance, which gives them an advantage in the short term.

In the initial periods, *Collective Decision* presents a lower performance than the *Authority*. This implies that, in the early periods of the adoption process, the omission errors weigh more than commission errors in the collective performance. When a new technology appears, many opportunities for improvement arise and decision mechanisms with more

Table 1
Scenario performance (*SV*) and its standard deviation (*SD*) in each period.

	Automatic System		*Authority*		*Collective Decision*							
	S		*A*		*C*1		*C*2-1		*C*2-2		*C*2-3	
Period	*SV*	*SD*	*SV*	*SD*	*SV*	*SD*	*SV*	*SD*	*SV*	*SD*	*SV*	*SD*
1	1.28	0.00	1.16	0.14	1.04	0.10	1.03	0.09	1.00	0.02	1.00	0.01
10	1.18	0.00	1.15	0.15	1.18	0.15	1.14	0.15	1.01	0.06	1.00	0.02
20	1.22	0.00	1.25	0.07	1.28	0.12	1.24	0.14	1.03	0.10	1.00	0.03
30	1.56	0.00	1.43	0.18	1.36	0.14	1.33	0.16	1.06	0.15	1.01	0.05
40	1.59	0.00	1.50	0.15	1.45	0.14	1.41	0.15	1.11	0.20	1.01	0.07
50	1.34	0.00	1.23	0.19	1.45	0.13	1.42	0.14	1.12	0.20	1.01	0.07
60	0.79	0.00	1.15	0.28	1.45	0.13	1.42	0.14	1.13	0.20	1.01	0.08
70	1.06	0.00	1.09	0.11	1.45	0.13	1.42	0.14	1.14	0.20	1.01	0.08
80	1.06	0.00	1.24	0.31	1.50	0.13	1.47	0.14	1.18	0.23	1.02	0.09
90	1.36	0.00	1.25	0.18	1.49	0.13	1.47	0.14	1.18	0.23	1.02	0.09
100	0.91	0.00	1.11	0.18	1.49	0.13	1.47	0.14	1.19	0.23	1.02	0.10

Note. Stronger background colors represent higher performance.

omission errors are penalized. Table 1 shows if the validity of the new technology is sufficiently long (40 periods in our case). *Collective Decision* with moderate resistance to innovation (*C*1 and *C*2-1) has an expected payoff of 1.45 and 1.41, which is almost 41% higher than that of the status quo and 16.67% (20/120) higher than the average payoff of the underlying technology. As time passes, the payoff from the last accepted project increases; therefore, the likelihood that a good project is rejected (omission error) decreases. This is because there will be fewer projects with a value higher than the current one and opportunities for improvement will be reduced. In this situation, *Collective Decision* across *C*1 and *C*2-1 scenarios has an advantage because of its ability to reduce commission errors (moderate resistance to innovation), avoid setbacks in performance, and allow the organization to systematically obtain better returns than under *Authority* (*A*). The *Authority*'s symmetry between commission and omission allows for rapid growth in performance. However, it is difficult for the *Authority* to maintain high-performance levels because of its inability to avoid commission errors. This analysis restricts the use of an authoritarian decision mechanism in sectors with constant technological changes.

Collective Decision presents limitations when the validity of the new technologies is ephemeral and the possible appearance of strong influences among individuals is a threat. The right side of Table 1 shows that medium connection levels between individuals (*C*2-2) considerably increase the validity period required by the *Collective Decision* to perform better than the *Authority*. To reduce the number of periods required for *Collective Decision* to perform better than the *Authority*, resistance to innovation must be moderate and have a low density of social ties that limit the possibility of social influence.

To more deeply analyze the results, we compute the average cumulative performance—the sum of the performance of a scenario up to period *t*, divided by the number of periods (*t*) (CSV_t^k). It shows when one scenario overcomes another, considering all the performances obtained up to that moment. Comparing the results for periods 10, 100, and 1000 provides information on the trends of the scenarios.

The fifth and sixth columns of Table 2 and Fig. 2 show how, in period 100, scenarios without any (*S* and *A*) and moderate resistance to innovation (*C*1 and *C*2-1) have an average of cumulative performance that is close to the value in period 1000. Their average of cumulative performance does not present a growing trend and most of the important growth takes place in the first 100 periods, presenting a clear concavity in the adoption process. The scenarios with greater social influence (*C*2-2 and *C*2-3) show slow growth with an increasing trend, with some concavity in case *C*2-2; however, in *C*2-3, it is more linear.

Fig. 2 shows how, in the short term, *Automatic System* (*S*) and the *Authority* (*A*) present the best performances. In fact, in Scenario *C*1, *Collective Decision* does not improve the cumulative performance average of *Automatic System* (*S*) until the 22nd period and the *Authority*

[4] Simulations were conducted with organizations of size N = 6, 13, 50, 100, and 500. The results show that, for sizes greater than 13, the probability of accepting the organization hardly changes.

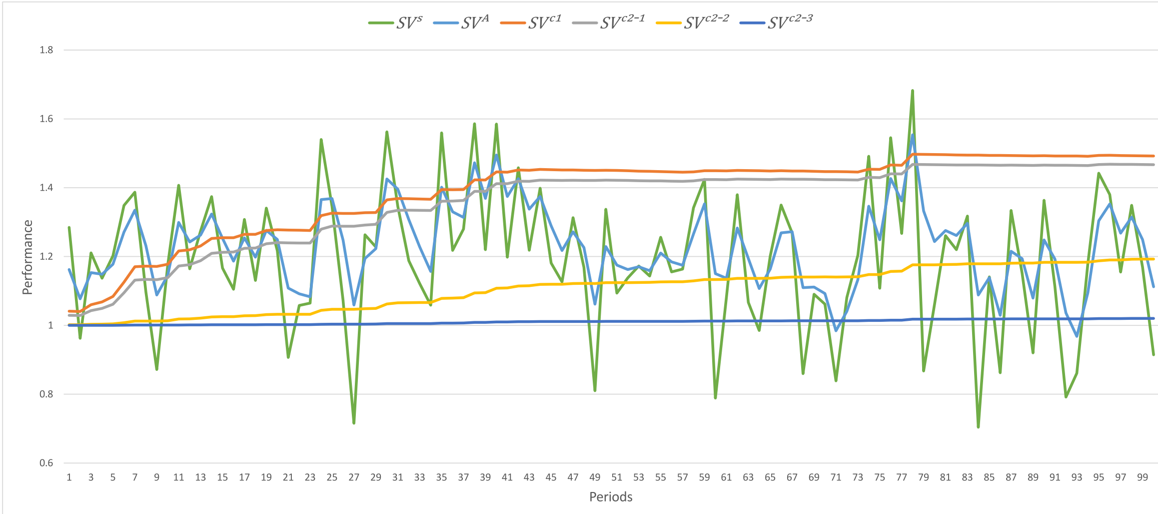

Fig. 1. Evolution of performance in different scenarios.

Table 2
Comparison of performance, average of cumulated performance, and number of changes in periods 10, 100 and 1000.

	Performance (*SV*)			Cumulative Performance (*CSV*)			Cumulative Changes (*SNA*)		
Period	10	100	1000	10	100	1000	10	100	1000
S	1.18	0.91	1.12	1.17	1.19	1.19	10.00	100.00	1000.00
A	1.15	1.11	1.14	1.18	1.23	1.23	4.44	48.51	490.01
*C*1	1.18	1.49	1.58	1.11	1.39	1.53	0.65	2.92	11.73
*C*2-1	1.14	1.47	1.57	1.08	1.36	1.51	0.49	2.41	8.92
*C*2-2	1.01	1.19	1.46	1.01	1.10	1.36	0.04	0.52	1.70
*C*2-3	1.00	1.02	1.16	1.00	1.01	1.09	0.00	0.05	0.40

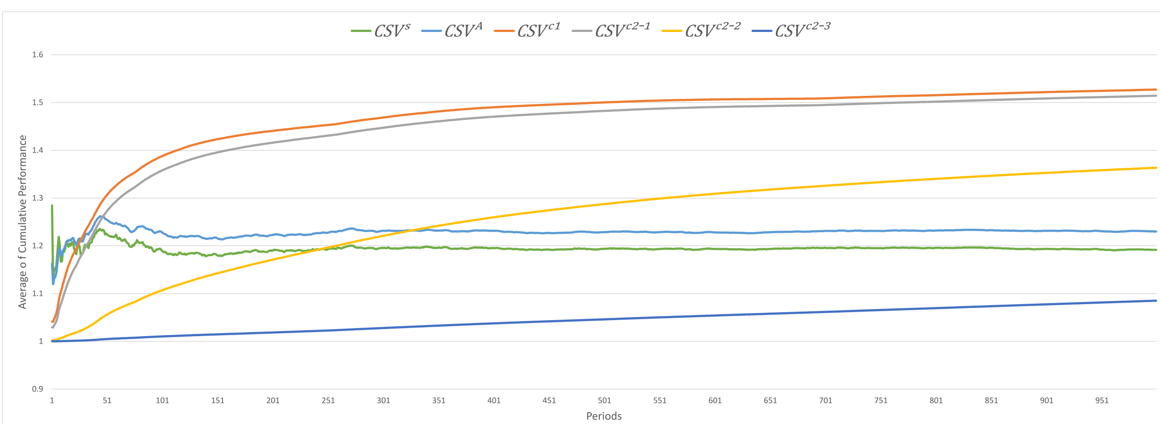

Fig. 2. Evolution of the average of cumulative performance in different scenarios.

(*A*) until the 27th period. Similarly, in Scenario *C*2-1, *Collective Decision* does not exceed *Automatic System* (*S*) until period 33 and the *Authority* (*A*) until project period 48. Notably, *Collective Decision* requires some innovation projects to obtain a better performance than *Authority*. This may be why a significant part of the literature has analyzed resistance to innovation as perverse.

In the long term, the *Collective Decision* scenarios with moderate resistance to innovation (*C*1 and *C*2-1) experience a significant gain in the average of cumulative performance, concerning the initial status quo. In period 1000, the scenario without social influence (*C*1) presents a gain of 53% over the initial status quo, while those with social influence and minimal density (*C*2-1) present a gain of 51%. The long-term scenario shows how social influence and medium density (*C*2-2) present an average of cumulative performance, which is 36% higher than that of the initial status quo; however, the cumulative performance of the *Authority* (*A*) is only 23% higher than that of the initial status quo. The scenarios with the lowest gains are *S* and *C*2-3, presenting an average cumulative performance of 19% and 9% above the initial status quo, respectively. The differences in the long-term scenarios are extremely important. The *Collective Decision* scenarios with moderate resistance to innovation (*C*1 and *C*2-1) have twice the cumulative performance gain than that of *Authority* (*A*), and the scenario with social influence and maximum density (as the maximum level of resistance to innovation) is the only one with a cumulative performance that is worse than *Authority* (*A*).

Each change implies accepting an innovation project that requires the organization to adapt. Implementing an innovation project involves initiating a learning process, adapting the organization, and losing the knowledge acquired about the previous status quo (entry and exit costs). When an organization bases its performance gains on accepting many innovation projects (many changes), it must manage additional costs (entry and exit costs), which entail more difficulty than retaining the status quo. The seventh, eighth, and ninth columns of Table 2 show the number of times the status quo has been replaced by an innovation project in the first 10 periods, 100 periods, and total number of periods (1000). The *Automatic System* (*S*) admits all innovation projects by definition; therefore, there is a change in each period. The *Authority* (*A*) presents half of the changes in the *Automatic System* (*S*)—around 49% of innovation projects are accepted. Across all scenarios, the *Collective Decision* shows a rate of acceptance that is less than 3% of the changes in the *Automatic System*. As the number of periods increases, the number of changes in *Collective Decision* tends to reduce. This decrease in changes as the periods increase confirms that resistance to innovation is enough for maintaining high-performance levels. Scenarios *C*1 and *C*2-1 admit 2–3% of the changes in the *Automatic System* (*S*) in the first 100 periods but this value is only 0.9–1% when the 1000 periods are considered. However, Scenario *C*2-2 admits less than two changes between the 1000 innovation projects and does not reach one change.

Collective Decision only admits changes that present a significant differential performance concerning the status quo, which nullifies the possibility of going backward (commission errors). The standard deviation of the *Collective Decision* is composed of greater differences in performance (simulations) but they are less likely. However, the standard deviation of the *Authority* is composed of smaller differences in performance (simulations) but they are more likely (for more detail see Figs. 5–11 of Appendix II). There is a major difference in the number of changes required to achieve each performance in each scenario. If the changes had some type of penalty that was not included in the performance, *Collective Decision* would present a substantial advantage over *Authority*. Managers must assess the expected performance and sacrifice of changes needed to obtain it, considering the temporal evolution of the two variables.

5. Discussion and conclusions

Rationally bounded individual makes mistakes in the evaluation of complex projects, such as technological innovation projects, where vast amounts of information are required. These mistakes are mainly of two types, namely, omission and commission errors. We show how different decision-making mechanisms favor one type of error over the other and its impact on the overall performance. Despite being simulated, the insights could be relevant for innovation management, particularly for designing decision mechanisms on adoption or rejection of innovation projects. Moreover, the simulation results show that *Collective Decision*'s disadvantage in high omission errors can be an advantage in a dynamic setting where the organization sequentially ponders innovation projects. It is expected that as time passes, the opportunity cost of preserving the status quo and resistance to change, which goes together with *Collective Decision*, will decrease. This is because the likelihood of receiving good projects that can be rejected with comparatively high probability also decreases over time.

All this is true for an established technology from which the evaluated projects originate, which could be described as incremental innovation. For organizations that rapidly implement technological changes and render the current underlying technologies obsolete, *Collective Decision* may not be a solution because there is no time to take advantage of the decreasing costs from higher omission errors. *Authority*, or letting a single bounded rational person make the decision, is beneficial in terms of low omission errors; organizational performance will be more volatile under *Authority* because, compared with *Collective Decision*, more projects that will eventually fail are accepted. However, if the period between the introduction of the current technology and a new and more disruptive technology (in our setting, a new random distribution for the value of the innovation) is relatively short, *Authority* is preferred to *Collective Decision* because the opportunity costs of omission errors are high in the early stages. Under *Collective Decision*, the more intense the social influences (the density of the network), the higher the likelihood of omission errors and lower the likelihood of commission errors. Hence, under sufficient social pressure, organizations are stuck in their status quo with no change at all.

5.1. Literature discussion

5.1.1. Decision mechanisms

Some technology project consultants (Asay, 2017; Venture Beat Staff, 2019) and academic authors (Beer and Nohria, 2000; Burnes, 2005) have proposed a solution to the high number of failed innovation projects (more than 80%). According to them, a gradual upward approach allows for a deeper discussion. Here, the participation of all members requires an evaluation of the integration of the project in all existing business and organizational processes (internal policy, lack of skills, security, etc.) (Dolata, 2009). Some empirical works have found a positive relationship between the success of innovation projects and participation in the decision-making stage (Cohn, 1981; Kim, 1980; Russell and Russell, 1992). Our theoretical results highlight that *Collective Decision* can present a performance that is superior to that of the *Authority*, reducing the number of failed projects. This aspect has not been theoretically explored in the literature. Moreover, intrinsic resistance to innovation also leads to the rejection of many profitable projects (omission errors) and reduces the number of adopted innovations (changes). The *Authority* tends to accept innovation projects that fail mainly because it does not consider all the idiosyncrasies of the organization that will manifest in the implementation stage. Therefore, managers may not be fully aware of the importance of employees and advantages of the *Collective Decision*, which includes a greater commitment from everyone.

We also show that a top-down approach based on *Authority* is preferred if short-term results are sought (Lee and Csaszar, 2020; Seshadri and Shapira, 2003). Technological projects could demonstrate these characteristics. Thus, the evidence that most CEOs follow a rapid, top-down approach in adopting technology projects could be consistent with the theoretical prediction if they act as the *Authority*. However, given that this strategy requires more changes in the organization, and some of them may fail. The simulated trajectories provide useful information on the performance evolution of each decision mechanism. In a contingent framework, the decision mechanism must consider internal organizational elements (capacities) and organizational environment. Research shows how individual evaluations are added to organizational decisions and how returns change over time. Managers must decide which mechanisms are better under given conditions (Christensen and Knudsen, 2010; Csaszar and Eggers, 2013; Davis et al., 2009; Hastie and Kameda, 2005). From an internal perspective, keeping social elements that affect decisions aside, not all organizations are equally prepared to adopt innovation projects (Heckmann et al., 2016). To achieve the average cumulative performance in each scenario indicated in Section 4, an organization must accept a certain number of innovation projects. The greater the number of accepted projects, the greater the number of innovations implemented to improve firm performance. The scenarios with the highest resistance to innovation achieve the specified performance level and adopt fewer innovation projects. Although the *Authority* may present more advantages than *Collective Decision* in the short term, its improvement model requires a considerably flexible organization and a willingness to innovate (Seo et al., 2017; Wright et al., 2012). This leads to significant fluctuations in performance, as shown in Fig. 1. However, the fact that trajectories of performance present different levels of dispersion in each scenario, different levels of uncertainty in organizational performance is implied. This shows that, in some scenarios, the obtained performance is more dependent on chance. For example, under *Collective Decision* without social influence ($C1$), we bear a greater probability of being far (above or below) from the average result of the scenario than in *Authority*. In this case, the uncertainty of the collective decision is less intuitive and more difficult to recognize.

5.1.2. Organizational elements

Studying the circumstances under which organizational characteristics, such as the number of social ties, affect the performance required to accept an innovation project (modifying the level of resistance), is relevant for organizational design. This is because it affects the expected performance of the *Collective Decision*. Our study finds that, when social ties imply influence in the judgment of individuals, the increase in network density increases resistance to innovation. This determining factor hurts hampers firm performance under *Collective Decision*. Next, we identify the underlying principles that produce these results and delve into their applicability.

5.1.3. Resistance to innovation

Given that *Collective Decision* requires the unanimity to adopt a project, it presents natural resistance, and a consequently higher level of project rejection. This resistance causes a double effect whose outcome is not intuitive. On the one hand, it increases omission errors, that is, projects that present a performance higher than the status quo are rejected. On the other hand, commission errors decrease, making it difficult to accept projects whose performance is lower than that under status quo. When faced with a technological innovation whose projects have an average performance that is greater than the status quo, one could think that this type of decision mechanism would obtain worse results than *Authority,* whose balance between omission and commission errors is symmetrical. However, we show that the cumulative performance gain of *Collective Decision* with some social influence is twice that of *Authority*.

Resistance to adoption under *Collective Decision* increases when individuals' judgments are influenced by their environment. Jones (2003) have argued that being aware of their own judgments and mistakes, makes individuals sensitive to the judgments of their environment, which is called "social influence" (Cialdini and Goldstein, 2004; Granovetter, 1978; Salganik et al., 2006). This resistance becomes especially important in the early discussions on *Collective Decision* when most individuals favor the status quo. Being a pioneer is hard when everyone thinks the same (Kandel and Lazear, 1992; Katz and Lazarsfeld, 2006). This explains why some authors have shown that, in environments with dense social ties between individuals, innovations mostly appear among the most isolated individuals (Fang et al., 2010). In the early stages, an innovative individual must try to convince another individual in their shared environment. This is easier in isolated environments than in highly connected environments, where social pressure limits the spread of novel ideas.

Although there are many studies on social ties, theoretical discussions on desirable properties for collective decision-making in the manifestation of undirected judgments that can originate in an organization, have received little recognition. In our case, the combination of unanimity resistance and social influence suggests that, from a medium connection (Scenarios $C2$-2 and $C2$-3), the returns from *Collective Decision* appear lower than those from *Authority* in the first 100 projects. This justifies the management or at least the identification of organizational elements such as social ties, density, et cetera. Expected opportunity losses from *Collective Decision* may justify an *Authoritarian* decision mechanism on organization with individuals with strong social influences. Furthermore, the comparative advantage of *Collective Decision* may be optimized when combined with low social influence.

5.1.4. Adoption process

Our study shows the importance of implementing dynamic adoption process in decision-making for innovation projects (Farzin et al., 1998; Ilori and Irefin, 1997; Wang et al., 2008). If managers are unaware of how *Collective Decision* works, the disparity in performance compared to other organizations with the same decision mechanism or the probability of omission errors, can be interpreted as a lack of commitment. This generates tensions in maintaining the decision-making participation mechanisms for long enough to provide positive performance, limiting the analysis to the short-term, which leads to myopic management of innovation.

5.2. Extension of the literature

Our study provides an original line of research in which the decision mechanisms applied to a dynamic process of adopting new technology are modeled. Our proposal is based on the literature that seeks group decision mechanisms to reduce the fallibility of individuals (Christensen and Knudsen, 2010, 2002; Csaszar, 2013; Knudsen and Levinthal, 2007; Sah and Stiglitz, 1986). Accordingly, this study incorporates a form of non-directed and spontaneous *Collective Decision* mechanism, similar to collective action in Marwell et al. (1988), Marwell and Oliver (1993) and Oliver et al. (1985), expanding and connecting two parts of the literature that had remained independent. For this purposed, the ABM methodology is a powerful tool to better understand the innovation performance of organizations. Moreover, this method allows to simulate the adoption decision process giving more information than conventional empirical research.

5.3. Limitations of the model and future lines of research

Our goal is to contribute a theory applicable to real organizations. In this section, we present the limitations of our results.

5.3.1. Homogeneity in individual capacities

We assume constant reliability of all members in an organization. Heterogeneity in the reliability of individuals could justify a higher performance of *Authority* if selection processes can identify the most reliable individual to act as the authority. Some studies (Chakraborty and Yılmaz, 2017; Dessein, 2002; Harris and Raviv, 2010, 2008, 2005) have suggested that it is optimal to assign decision-making to the *Authority* when it has privileged information relevant to the organization. When groups are homogeneous, all individuals are interchangeable and *Collective Decision* results is a function of the number of ties per individual. Conversely, in a heterogeneous group, innovation proposals, number of ties, and individuals' ability to process information are all important because one person may be able to contribute much more than another (Marwell et al., 1988). Our model can easily include reliability heterogeneity, but new parameters would have to be introduced into the individual decision probability function.

5.3.2. Homogeneity in social networks

We consider different social networks where all members have the same number of homogeneous and undirected social ties. We could easily change to a non-homogeneous network (density and centrality). Then, where the innovation appears under *Collective Decision* would be relevant, because the probability of adopting the innovation depends on the number of pioneer's contacts. We could also consider that there are social ties with different forces. Granovetter (1973) has argued that strong ties tend to form groups when it is difficult for individuals to disagree, while weak ties tend to bridge groups. Therefore, weak ties are a better basis for examining *Collective Decision*. However, in this study, the main reason for the better performance of *Collective Decision* is the independence of judgment, which is better achieved with weak social ties. Our results imply that it is not weak ties, per se, that are useful but their lesser influence on individual judgment. In a world of bounded rationality, one way to improve individual judgments is to allow more reliable individuals to have more influence, even though this situation seems to favor authoritarian mechanisms.

Furthermore, the current information technology allows us to assume that establishing or using a social tie is cost-free (Castells and Castells, 2010; van Alstyne, 1997). However, it is possible to measure the number of discussions necessary to reach a group decision and assign some costs to them. A natural extension of the model would be to consider these costs (Marwell et al., 1988).

5.3.3. Non-strategic behavior

Our model considers no strategic behaviors—all individuals try to maximize group performance and their errors are the consequence of bounded rationality and not individual interests. An interesting extension would be to introduce asymmetry in the perceived benefits of the innovation so that not all individuals share the same interest in accepting the project. It is also possible to include the cost of resources (time and money) available to individuals. The effects of the combination of individual asymmetric costs and benefits of *Collective Decision* for obtaining collective goods, has been the basis of a line of research (Marwell et al., 1988; Marwell and Oliver, 1993; Oliver et al., 1985).

5.3.4. Unanimity as a rule of acceptance

The proposed model requires unanimity to adopt an innovation project. This rule can be replaced by another in which the group adopts an innovation as soon as a simple majority in favor of the adoption is reached. Unanimity requires that all individuals in the organization win. However, majority systems may be interested in adopting projects that, even though they imply losses for the organization, represent gains in the individual balance of the majority. This situation is possible when the losses of the individuals in the minority are greater than the losses supposed by the innovation project for the organization.

5.3.5. Future lines of research

The combination of the effects of *Collective Decision* on the individual and network heterogeneities, strategic behavior, and decision rules can only be replicated in a simulated environment because these interactions are unobservable. Given that no real data is available on this, ABMs help to understand the surprisingly direct and indirect relationships and allow the isolation of the conjunction of several probabilistic events. Incorporating the aforementioned items into our model may be a promising line of research. The inclusion of strategic behavior opens the opportunity to study strategies (in the sense of game theory) that maximize the expected results of individuals despite potential losses for the organization.

5.4. Conclusions

We study two decisions mechanisms in an organization that must repeatedly decide on adopting innovation projects that can change the status quo. Given sufficient time to select a sustainable growth path, *Collective Decision*, as modeled here, results in superior organizational performance than *Authority* under the following two conditions: the underlying technology that generates successive innovation projects last sufficiently long and the *Collective Decision* protects itself from moderate and strong social influence that characterizes interpersonal informal relationships in groups.

Collective Decision selects a performance growth path where, as the performance under the status quo improves, the current technology is less likely generate high-value projects. Second, the organization is less likely make commission errors in accepting projects with a value lower than the status quo. The described situation resembles that of organizations' "resistance to innovation"—the number of innovation projects rejected is higher than that expected at the outset. The resistance to innovation resulting from *Collective Decision* that evolves toward reducing the commission errors by increasing the likelihood of a project being rejected over time, is positive in terms of organizational performance (Burnes, 2015; Dziallas and Blind, 2019). This holds only if the social influence of peers' opinions on their own acceptance decision is sufficiently low; otherwise, resistance to innovation turns into a paralysis of innovation.

Data availability

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

Acknowledgments

To Professor Sala-Fumás for discussing this study and for his permanent and disinterested help. To Reviewer 1 for her/his patience and detail in her/his work, providing a constructive review of this study essential for its improvement.

This work was supported by the Spanish Ministerio de Economía y Competitividad, grants ECO2017-86305-C4-3-R, PGC2018-096026-B-I00 and PID2021-122961NB-I00, Diputación General de Aragón (DGA) and European Social Fund, grants CREVALOR and E22-20R.

Appendix I. ABM model

The process begins when an individual introduces an innovation project and communicates with a neighbor. After each debate (interaction) between two individuals who are connected where one is in favor of the status quo and the other in favor of innovation, one and only one of them changes his position, changing the judgment map for the next iteration. Thus, any individual with a different judgment with respect to someone from their environment will confront this position with one of their discordant neighbors chosen at random. In each iteration, as many interactions as possible will be carried out, considering that each individual can only perform an interaction with a single neighbor by iteration. There is no limitation on the number of times individuals can change their judgments throughout the process.

When there is social influence, the success probability in the first iteration is given by equation (3) with $nb_{c,i} = 1$; the probability that the pioneer abandons his attempt to innovate and remains in the status quo is given by equation (4) also with $nb_{c,i} = 1$. These probabilities show that the number of individual connections has a great influence on the success of acceptance or failure of the innovation proposal: a high number (low) means greater (less) resistance to adopting the innovation proposal since in that initial moment there are no individuals in favor of proposed innovation project apart from the pioneer.

If the first interaction result is that both interlocutors are convinced to innovate, a new interaction is initiated. This time, two individuals in favor of innovation will interact simultaneously with each one of their influencing groups who is not in favor, until they finish all the possible interactions. Once the cycle is over, whether everyone is convinced in one way or another will be known, or if there is still someone who disagrees with the rest. In the first case the process ends and whether it is an accept or reject will be known according to the alternative in which unanimity is specified. In the second, when there are discrepancies, a new iteration is restarted, and so on. Mathematically, this process is represented by a Markov chain, whose state space is all the possible configurations of individuals favorable to innovation versus supporters of the status quo, and the described transition probabilities do not depend on iteration. Given that the network considered is non-directed, there are only two absorbing states, all favorable to innovation or all against, the rest being transitory states so that the probability of reaching an absorbent state is 1. The calculation of the probabilities of acceptance or not, that is, accept or reject of innovation is obtained by the Monte Carlo method.

The process of dissemination and social influence among individuals being studied acquires its maximum realism in relatively small groups, where it can occur both in a formal and informal organizational structure. Fig. 3 allows us to compare the probability in scenarios with resistance to innovation, that requires unanimity, versus the probability of authority's decision, for different economic values of innovation against the status quo, $V^c - V^s$, (abscissa axis). We observe how the *Collective Decision* mechanism a lower probability of acceptance than the *Authority* mechanism.

Given a difference in value with respect to the innovation of $-0.26 = (V^c - V^s)$ the rejection probability in *Collective Decision* without social pressure ($C1$), in low density network ($C2$-1), in a medium density network ($C2$-2), and in high density network ($C2$-3) is around 99%, compared to that of the *Authority* (A), which is only 57%, that is, the probability that the *Authority* accepts an innovation proposal whose performance is lower than the status quo is much higher than any of other mechanisms (commission errors). In turn, the minimum required difference of relative performance to obtain a rejection probability of 50% is $0.5 = (V^c - V^s)$ in a *Collective Decision* without social pressure ($C1$), whereas it is $1 = (V^c - V^s)$ in low density network ($C2$-1), $2 = (V^c - V^s)$ in medium density network ($C2$-2) and more than $2.5 = (V^c - V^s)$ for a high density network ($C2$-3), while the *Authority* (A) rejects 50% when there is no difference between alternatives value ($V^c = V^s$), that is, that the *Authority* shows far fewer errors when the innovation value is higher than the status quo value (omission errors). The scenarios that show the greater resistance are those whose representation is located more to the right in Fig. 3. A Sigmoid slope that draws resistance to innovation has an inverse relationship with the commission error that is made when deciding.

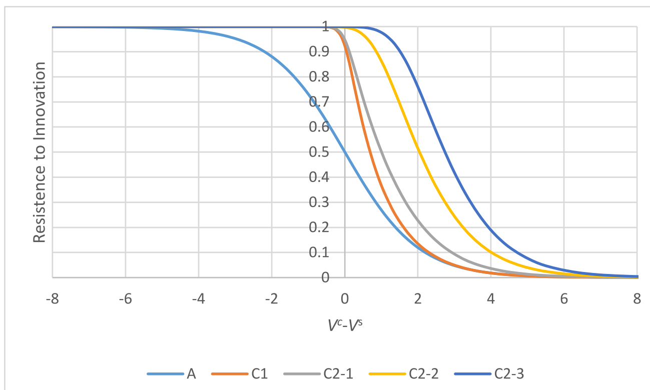

Fig. 3. Resistance to innovation in decision mechanism (rejecting probability of innovation proposal).

Appendix II. Simulation of the adoption process

Each simulation faces a fixed sequence of 1000 unalterable innovation projects ($V_1^c = 1.28, V_2^c = 0.96, \ldots, V_{1000}^c = 1.12$) sampled from a normal distribution with a mean of 1.2 and a standard deviation of 0.2. In period $t = 0$ all simulations start from a performance of the status quo $V_0^s = 1$. This appendix details the 100000 simulations performed ($g = 1, \ldots, 100000$) for each scenario k. This level of detail allows a deep understanding of the results of the scenarios. In scenario k, we denote by $\{V_{g,t}^k > 0 : t = 0, \ldots, 1000\}$ the performance of simulation g in period t. Simulation g provides one performance in each period (after each innovation project is evaluated) according to a specific probability $p(e^{V^s} / e^{V^c} | k) = p(e^{V_{g,t-1}^k} / e^{V_t^c})$ that depends on the difference between previous performance and innovation project. The simulations represent the absolute frequency of the possible performances of scenario k in period t.

Each simulation generates a trajectory of simulation performance $\{V_{g,1}^k, V_{g,2}^k, \ldots, V_{g,1000}^k\}$—a sequence of acceptances (changes) and rejections of 1000 evaluated innovation projects (1000 periods). Therefore, each simulation is a possible trajectory for an organization of scenario k. Some trajectories are more probable than others, this is represented when more than one simulation g presents the same trajectory. Further, we define for simulation g the average cumulative performance up to each period (denoted as $CV_{g,t}^k = \sum_{h=1}^{t} V_{g,h}^k / t$) and the number of cumulative "changes" (acceptances) up to each period (denoted as $NA_{g,t}^k$).

By repeating the process 100000 times (100000 simulations) within the same scenario that faces the same sequence of innovation projects, the scenario information is obtained. The performance of a scenario in a specific period (after evaluating the corresponding innovation project) is the average of the performances presented by all the simulations in that period ($SV_t^k = \frac{1}{100000} \sum_{g=1}^{100000} V_{g,t}^k$), its standard deviation represents the deviations of the performance of the simulations concerning the performance of the scenario in that specific period ($SD_t^k = \sqrt{\frac{1}{100000} \sum_{g=1}^{100000} (V_{g,t}^k - SV_t^k)^2}$), its average cumulative performance up to each period ($CSV_t^k = \sum_{h=1}^{t} SV_h^k / t$), and the number of cumulative changes up to each period ($SNA_t^k = \frac{1}{100000} \sum_{g=1}^{100000} NA_{g,t}^k$). Therefore, simulations are an instrument that allows us to obtain the idiosyncratic probabilities of each period without the need for a closed formula.

To see the difference between the performance of a V_t^k simulation and the performance of an SV_t^k scenario, we go to Fig. 4 where shows the first four possible acceptance and rejection steps in the conditions established in scenario k. A simulation g will only present a trajectory of those expressed in the figure. As explained at the beginning of Section 3, an organization in scenario k shows a probability of accepting $p(e^{V^s} / e^{V^c} | k)$, and decides period by period which projects it accepts and which it rejects. As we can see in Fig. 4, it is easy to obtain a closed formula for the scenario performance at period 1, $SV_1^k = p(e^1 / e^{1.28} | k) \cdot 1.28 + [1 - p(e^1 / e^{1.28} | k)] \cdot 1$. However, at period 2, it is, $SV_2^k = p\left(\frac{e^1}{e^{1.28}} \middle| k\right) \cdot p\left(\frac{e^{1.28}}{e^{0.96}} \middle| k\right) \cdot 0.96 + p\left(\frac{e^1}{e^{1.28}} \middle| k\right) \cdot \left[1 - p\left(\frac{e^{1.28}}{e^{0.96}} \middle| k\right)\right] \cdot 1.28 + \left[1 - p\left(\frac{e^1}{e^{1.28}} \middle| k\right)\right] \cdot p\left(\frac{e^1}{e^{0.96}} \middle| k\right) \cdot 0.96 + \left[1 - p\left(\frac{e^1}{e^{1.28}} \middle| k\right)\right] \cdot \left[1 - p\left(\frac{e^1}{e^{0.96}} \middle| k\right)\right] \cdot 1$. As can be seen, obtaining a closed formula in general is unfeasible. The idiosyncratic probabilities prevent the existence of a closed probability equation, and the scenario performance must be obtained by simulation.

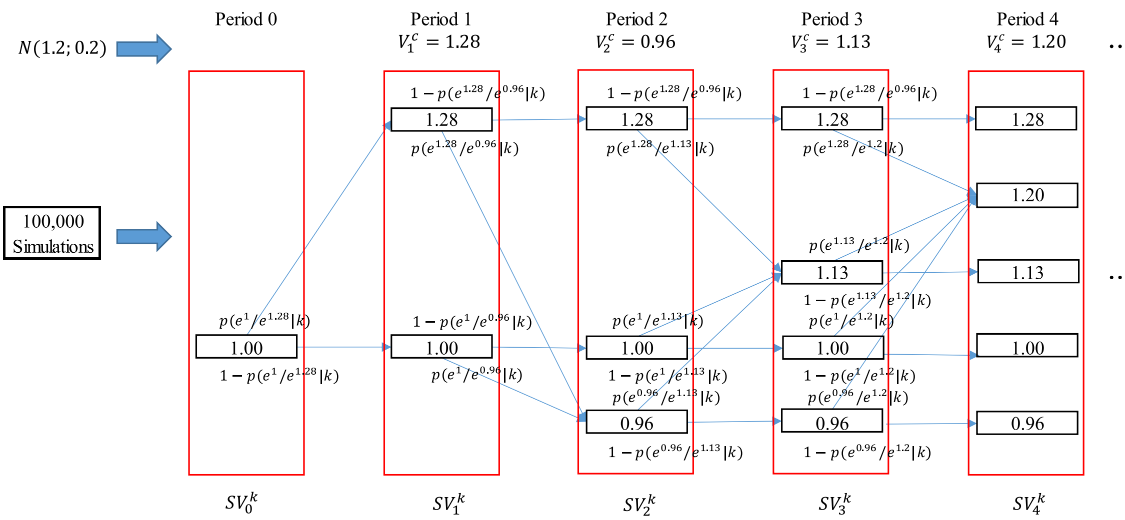

Fig. 4. Diagram of scenario k calculation performance in the first four periods (innovation projects) SV_t^k.

The simulation obtains the absolute frequency of possible returns at period t. For simulation g in t the value of the status quo is the performance of the previous period of this simulation is $V_t^s = V_{g,t-1}^k$. The probability that simulation g change its performance at period t (accept the innovation project) can be rewritten as $p(e^{V^s}/e^{V^c}|k) = p(e^{V_{g,t-1}^k}/e^{V_t^c})$, in the same way the probability of rejecting is now $1 - p(e^{V_{g,t-1}^k}/e^{V_t^c})$. These probabilities are idiosyncratic, that is, it depends on the previous period t (specific due to the difference between the performance of each innovation project (fixed) and the simulation performance of the previous period). If the simulation accepts the innovation project t, then $V_{g,t}^k = V_t^c$, and if it is rejected, $V_{g,t}^k = V_{g,t-1}^k$. The simulation performance ($V_{g,t}^k$) is one possible result of a trial. Each possible performance of a particular trial at period t is unique, and different performances ($V_t^c; V_{g,t-1}^k$) are mutually exclusive (only one performance will occur on each simulation and period). In the adoption process, a simulation g adopts a sequence of 1000 decisions (sequence of acceptances and rejections) that are specified in one sequence of 1000 performances, one for each period $\{V_{g,1}^k, V_{g,2}^k, \ldots, V_{g,1000}^k\}$, which we call trajectory of simulation performance.

In this way, when the decision is made by the *Automatic System* (S), $p(e^{V^s}/e^{V^c}|S) = 1$ for all simulations and all periods, while for *Authority* (A) and *Collective Decision* (C), $p(e^{V^s}/e^{V^c}|k)$ is specific for each organization and period. When the result comes from *Authority* $p(e^{V^s}/e^{V^c}|A) = p_A = \left(\frac{e^{V_{g,t-1}}}{e^{V_t^c}} + 1\right)^{-1}$ has a closed form (1); when the result comes from *Collective Decision* is sought, the ABM introduces the innovation project in an individual who contacts another individual in his environment at random and begins the contagion process, moving freely within the organization with the only restriction of social ties giving a probability of scenario $p(e^{V^s}/e^{V^c}|C)$ that was obtained in a previous simulation process (details in Appendix I).

Fig. 5 shows a simple version, and its construction is detailed. In this case, we show four trajectories of simulation performance instead of the 100000 conducted for the first 10 innovation projects (periods) ($V_1^c = 1.28, V_2^c = 0.96, \ldots, V_{10}^c = 1.18$) in scenario k. The upper panel shows the four trajectories of the simulation performance $\{V_{g,t}^k; g = 1, \ldots, 4; t = 1, \ldots, 10\}$, and the lower panel shows a diagram like the one in the rest of the figures. In the top panel, four simulations ($g = 1$, blue; $g = 2$, red; $g = 3$, orange; $g = 4$, green) and a series of innovation projects (dashed black line) are presented. Hence, the results obtained from the simulations could be different. All simulations start with the same performance level $V_0^s = 1$. In the first period, all simulations receive the first innovation project with a latent performance of 1.28 ($V_1^c = 1.28$). The probability of accepting this project is the same for the four simulations ($p(e^1/e^{1.28}|k)$). In our case, two simulations accept the innovation project ($g = 1,2$, blue and red), and two others do not ($g = 3,4$) (trajectories have been moved a bit to make them visible). In the second period, the red and blue simulations present a performance of 1.28 ($V_{1,1}^k = 1.28$; $V_{2,1}^k = 1.28$), and the new innovation project has a latent performance of 0.96 ($V_2^c = 0.96$); therefore the probability of accepting it is $p(e^{1.28}/e^{0.96}|k)$ (for simulations blue and red). Conversely, the green and orange simulations have a probability of accepting $p(e^1/e^{0.96}|k)$ (which is greater than $p(e^{1.28}/e^{0.96}|k)$). In this case, the green and red simulations make a mistake in accepting this innovation project. We continue this method to obtain a different trajectory for the simulation performance. Again, we may have moved them slightly to observe the concurrent routes. In period 4, the orange simulation accepts an innovation project (change) whose performance is lower than the status quo, which is a commission error. The green simulation rejects the innovation project whose performance exceeds that of the status quo, resulting in an omission error. The dashed black line is the performance of Scenario S, which is the underlying performance of the project.

The bottom panel shows the number of concurrent trajectories of the simulation performance with the thickness of the stroke: the thicker the stroke, the more trajectories that traverse that line. Therefore, it is the probability that this performance occurs in the scenario. The fixed performance of the innovation projects is shown in red. The average of all organizational performances in each period (innovation project) is drawn in blue (scenario performance, SV_t^k); the area shaded in blue is the standard deviation of simulation performance (standard deviation of scenario performance SD_t^k).

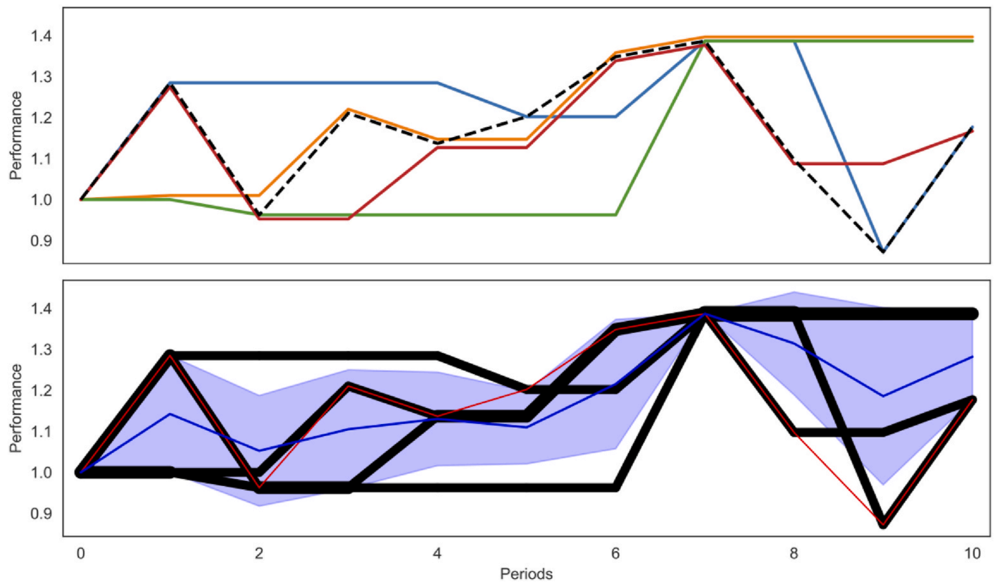

Fig. 5. Trajectories of simulation performance

This approach allows us to distinguish between the different trajectories of simulation performance in a scenario and the number of changes that each trajectory of the simulation performance presents. The performance balance by period (innovation project) for each scenario provides the dynamics of its adoption curve.

Figs. 6–11 present the simulation and scenario performances for the first 100 periods. Scenario *S* is represented in all graphs as a reference case. These figures are relevant because they show the different trajectories of simulation performance (black lines) that each decision mechanism goes through depending on the scenario. They show the mean, the composition of the standard deviation, and the number of projects accepted (changes) required to obtain each performance. The scenario performance represents the expected return of its characteristics; however, the trajectory of the simulation performance (g) can be any of the black lines, where the thickness indicates its likelihood.

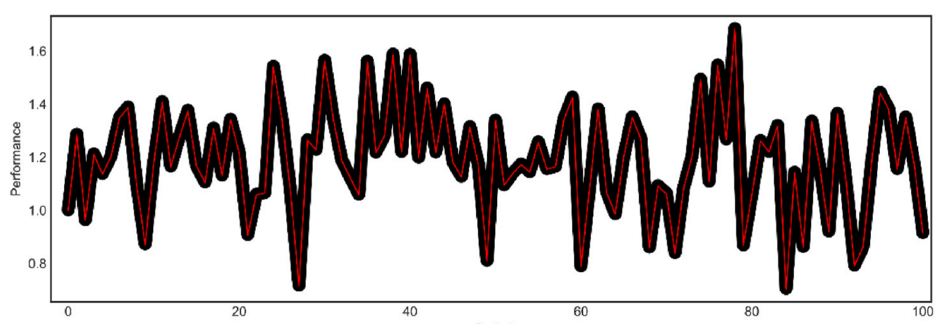

Fig. 6. Performance simulation of Scenario *S* in the first 100 periods

Fig. 6 shows the *Automatic System* (*S*) scenario, where the standard deviation is always zero because only the trajectory is drawn based on the performance of the innovation projects. This assumes that there will be no random performance differences in any period of the trajectory of simulation performance. Organizations must be able to manage the maximum number of changes possible because there is a change in every period. These characteristics make it a good reference scenario.

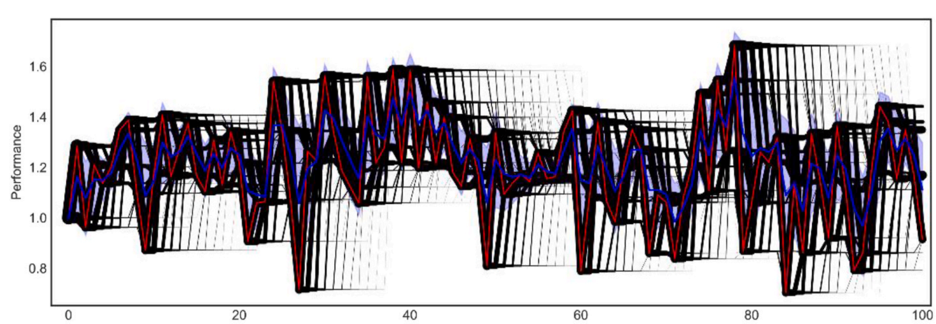

Fig. 7. Performance simulation of Scenario *A* in the first 100 periods

Figs. 6 and 7 show that *Automatic System* and *Authority* are scenarios with the least dispersion concerning their mean. In the *A* scenario

(Fig. 7), the trajectory of simulation performance barely shows persistence (permanence in performance without accepting changes) and tend to group quickly. This is because *Authority* accepts the proposals with some ease. Regardless of their previous decisions, they tend to accept innovation projects; their standard deviation of the scenario performance is the consequence of many small differences from the mean. In *Authority* scenario the simulation performances are not likely to be far from the scenario performance, but, in turn, it requires numerous changes. As it accepts many innovation projects, the organization should be flexible and able to manage changes well.

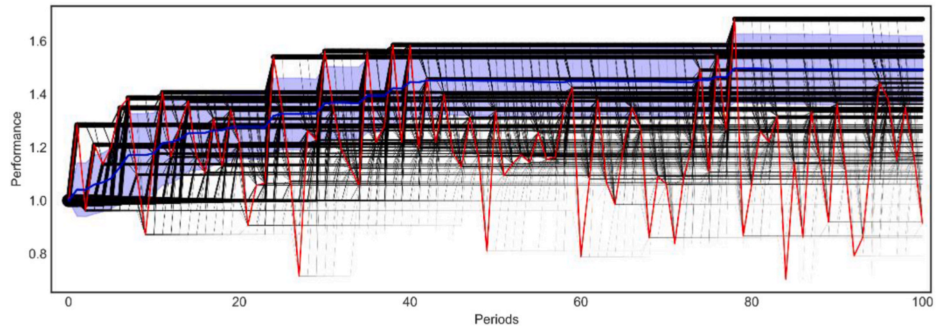

Fig. 8. Performance simulation of Scenario $C1$ in the first 100 periods

Fig. 8 shows the *Collective Decision* in the scenario without social influence ($C1$), which presents a substantial performance gain concerning *Automatic System* and *Authority* in the medium and long terms. It shows a greater persistence in its trajectories of simulation performance and requires fewer changes, especially when achieving high performance early. Persistence also entails maintaining the differences in performance that appear between trajectories of the simulation. Therefore, its standard deviation is because of a few changes but with a significant difference in the performance level. It is appreciable how the persistence in the initial return (performance 1) progressively changes to high performance (thicker lines are observed in the higher performances).

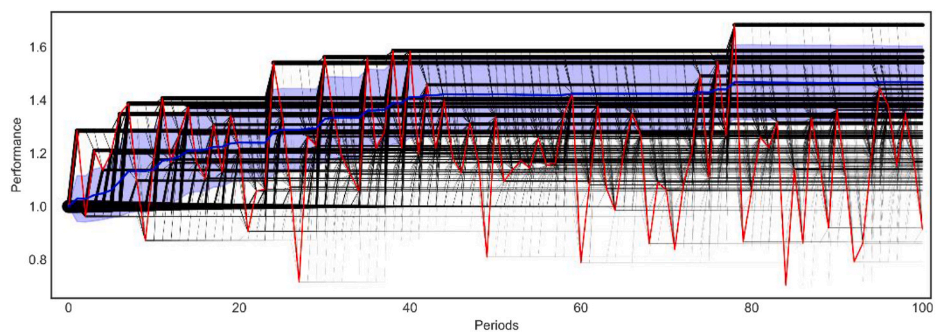

Fig. 9. Performance simulation of Scenario $C2$-1 in the first 100 periods

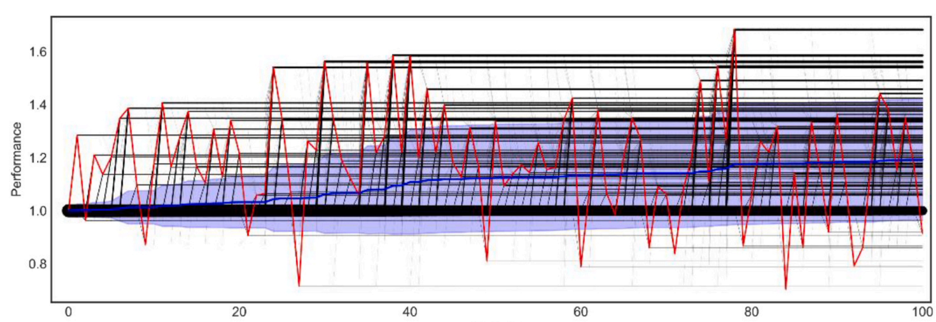

Fig. 10. Performance simulation of Scenario $C2$-2 in the first 100 periods

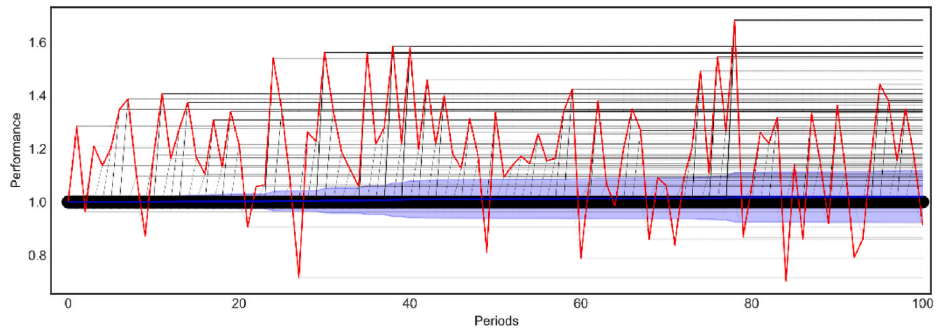

Fig. 11. Performance simulation of Scenario *C*2-3 in the first 100 periods

The introduction into *Collective Decision* of social influence between individuals with medium and high density (Scenarios *C*2-2 and *C*2-3) implies a significant deterioration in scenario performance. This is because social influence increases as social ties increase, resulting in resistance to innovation and persistence of trajectories of simulation performance. Figs. 10 and 11 show that most trajectories of the simulation performance remain with performance 1, showing the greatest thickness. At the extreme, the *C*2-3 scenario presents a situation of immobility concerning the status quo. The performance of the *Collective Decision* in Scenario *C*2-1 (minimum density) presents a good performance like that obtained in Scenario *C*1; Fig. 9 is considerably like Fig. 8.

References

Adler, P.S., Clark, K.B., 1991. Behind the learning curve: a sketch of the learning process. Manag. Sci. 37, 267–281. https://doi.org/10.1287/mnsc.37.3.267.

Arrow, K.J., 1963. Social Choice and Individual Values. Yale university press.

Asay, M., 2017. 85% of big data projects fail, but your developers can help yours succeed [WWW Document]. TechRepublic, 6.5.20. https://www.techrepublic.com/article/85-of-big-data-projects-fail-but-your-developers-can-help-yours-succeed/.

Balasubramanian, N., Lieberman, M.B., 2009. Industry learning environments and the heterogeneity of firm performance. Strat. Manag. J. 31, 390–412. https://doi.org/10.1002/smj.816.

Bass, F.M., 1969. A new product growth for model consumer durables. Manag. Sci. 15, 215–227. https://doi.org/10.1287/mnsc.15.5.215.

Beer, M., Nohria, N., 2000. Cracking the code of change. HBR's 10 must reads on change 78, 133–141.

Borgatti, S.P., Everett, M.G., 2006. A Graph-theoretic perspective on centrality. Soc. Network. 28, 466–484. https://doi.org/10.1016/j.socnet.2005.11.005.

Buchanan, J.M., Tullock, G., Buchanan, J.M., 1962. The Calculus of Consent: Logical Foundations of Constitutional Democracy. The collected works of James M. Buchanan. Liberty Fund, Indianapolis.

Burnes, B., 2015. Understanding resistance to change – building on coch and French. J. Change Manag. 15, 92–116. https://doi.org/10.1080/14697017.2014.969755.

Burnes, B., 2005. Complexity theories and organizational change. Int. J. Manag. Rev. 7, 73–90. https://doi.org/10.1111/j.1468-2370.2005.00107.x.

Burnes, B., Cooke, B., 2013. Kurt Lewin's field theory: a review and Re-evaluation. Int. J. Manag. Rev. 15, 408–425. https://doi.org/10.1111/j.1468-2370.2012.00348.x.

Castells, M., Castells, M., 2010. The Rise of the Network Society, 2nd ed., with a New Pref. Ed, the Information Age : Economy, Society, and Culture. Wiley-Blackwell, Chichester, West Sussex ; Malden, MA.

Catalani, M.S., Clerico, G.F., 1996. How and when unanimity is a superior decision rule. In: Decision Making Structures, Contributions to Management Science. Physica-Verlag HD, Heidelberg, pp. 15–29. https://doi.org/10.1007/978-3-642-50138-8_2.

Chakraborty, A., Yılmaz, B., 2017. Authority, consensus, and governance. Rev. Financ. Stud. 30, 4267–4316. https://doi.org/10.1093/rfs/hhx068.

Christensen, M., Knudsen, T., 2010. Design of decision-making organizations. Manag. Sci. 56, 71–89. https://doi.org/10.1287/mnsc.1090.1096.

Christensen, M., Knudsen, T., 2002. The Architecture of Economic Organization: toward a General Framework. University of Southerm Denmark, Odensen.

Cialdini, R.B., Goldstein, N.J., 2004. Social influence: compliance and conformity. Annu. Rev. Psychol. 55, 591–621. https://doi.org/10.1146/annurev.psych.55.090902.142015.

Cohn, S.F., 1981. Adopting innovations in a technology push industry. Res. Manag. 24, 26–31. https://doi.org/10.1080/00345334.1981.11756687.

Csaszar, F.A., 2013. An efficient frontier in organization design: organizational structure as a determinant of exploration and exploitation. Organ. Sci. 24, 1083–1101. https://doi.org/10.1287/orsc.1120.0784.

Csaszar, F.A., Eggers, J.P., 2013. Organizational decision making: an information aggregation view. Manag. Sci. 59, 2257–2277. https://doi.org/10.1287/mnsc.1120.1698.

Dam, K.V., Oreg, S., Schyns, B., 2008. Daily work contexts and resistance to organisational change: the role of leader–member exchange, development climate, and change process characteristics. Appl. Psychol. 57, 313–334. https://doi.org/10.1111/j.1464-0597.2007.00311.x.

Davis, J.P., Eisenhardt, K.M., Bingham, C.B., 2009. Optimal structure, market dynamism, and the strategy of simple rules. Adm. Sci. Q. 54, 413–452. https://doi.org/10.2189/asqu.2009.54.3.413.

Dent, E.B., Goldberg, S.G., 1999. Challenging "resistance to change". J. Appl. Behav. Sci. 35, 25–41. https://doi.org/10.1177/0021886399351003.

Dessein, W., 2002. Authority and communication in organizations. Rev. Econ. Stud. 69, 811–838. https://doi.org/10.1111/1467-937X.00227.

Dodds, P.S., Watts, D.J., 2005. A generalized model of social and biological contagion. J. Theor. Biol. 232, 587–604. https://doi.org/10.1016/j.jtbi.2004.09.006.

Dolata, U., 2009. Technological innovations and sectoral change: transformative capacity, adaptability, patterns of change: an analytical framework. Res. Pol. 38, 1066–1076. https://doi.org/10.1016/j.respol.2009.03.006.

Du, J., Love, J.H., Roper, S., 2007. The innovation decision: an economic analysis. Technovation 27, 766–773. https://doi.org/10.1016/j.technovation.2007.05.008.

Dubrin, A., Ireland, R., 1993. Management and Organization. Elsevier.

Dziallas, M., Blind, K., 2019. Innovation indicators throughout the innovation process: an extensive literature analysis. Technovation 80–81, 3–29. https://doi.org/10.1016/j.technovation.2018.05.005.

Esser, J.K., 1998. Alive and well after 25 Years: a review of groupthink research. Organ. Behav. Hum. Decis. Process. 73, 116–141. https://doi.org/10.1006/obhd.1998.2758.

Fang, C., Lee, J., Schilling, M.A., 2010. Balancing exploration and exploitation through structural design: the isolation of subgroups and organizational learning. Organ. Sci. 21, 625–642. https://doi.org/10.1287/orsc.1090.0468.

Farjoun, M., 2010. Beyond dualism: stability and change as a duality. AMR (Adv. Magn. Reson.) 35, 202–225. https://doi.org/10.5465/amr.35.2.zok202.

Farzin, Y.H., Huisman, K.J.M., Kort, P.M., 1998. Optimal timing of technology adoption. J. Econ. Dynam. Control 22, 779–799. https://doi.org/10.1016/S0165-1889(97)00097-3.

Fioretti, G., 2013. Agent-based simulation models in organization science. Organ. Res. Methods 16, 227–242. https://doi.org/10.1177/1094428112470006.

Ford, J.D., Ford, L.W., D'Amelio, A., 2008. Resistance to change: the rest of the story. AMR (Adv. Magn. Reson.) 33, 362–377. https://doi.org/10.5465/amr.2008.31193235.

Freeman, L.C., 1978. Centrality in social networks conceptual clarification. Soc. Network. 1, 215–239.

Freeman, L.C., Borgatti, S.P., White, D.R., 1991. Centrality in valued graphs: a measure of betweenness based on network flow. Soc. Network. 13, 141–154. https://doi.org/10.1016/0378-8733(91)90017-N.

Frishammar, J., Kurkkio, M., Abrahamsson, L., Lichtenthaler, U., 2012. Antecedents and consequences of firms' process innovation capability: a literature review and a conceptual framework. IEEE Trans. Eng. Manag. 59, 519–529. https://doi.org/10.1109/TEM.2012.2187660.

Furst, S.A., Cable, D.M., 2008. Employee resistance to organizational change: managerial influence tactics and leader-member exchange. J. Appl. Psychol. 93, 453–462. https://doi.org/10.1037/0021-9010.93.2.453.

Granovetter, M., 1978. Threshold models of collective behavior. Am. J. Sociol. 83, 1420–1443. https://doi.org/10.1086/226707.

Granovetter, M.S., 1973. The strength of weak ties. Am. J. Sociol. 78, 1360–1380. https://doi.org/10.1086/225469.

Griffin, R.W., 1993. Management. Mason, OH, Australia. In: Hardin, R. (Ed.), Collective Action. Published for Resources for the Future by the Johns Hopkins University Press, Baltimore, 1982.

Hardin, R., 1982. Collective Action. Johns Hopkins University Press.

Hardy, C., Clegg, S., 2004. Power and change. In: Boonstra, J.J. (Ed.), Dynamics of Organizational Change and Learning. John Wiley & Sons Ltd, England, UK, pp. 343–366. https://doi.org/10.1002/9780470753408.ch17.
Harris, M., Raviv, A., 2010. Control of corporate decisions: shareholders vs. Management. Rev. Financ. Stud. 23, 4115–4147. https://doi.org/10.1093/rfs/hhq081.
Harris, M., Raviv, A., 2008. A theory of board control and size. Rev. Financ. Stud. 21, 1797–1832. https://doi.org/10.1093/rfs/hhl030.
Harris, M., Raviv, A., 2005. Allocation of decision-making authority. Rev. Finance 9, 353–383. https://doi.org/10.1007/s10679-005-2263-z.
Hastie, R., Kameda, T., 2005. The robust beauty of majority rules in group decisions. Psychol. Rev. 112, 494.
Heckmann, N., Steger, T., Dowling, M., 2016. Organizational capacity for change, change experience, and change project performance. J. Bus. Res. 69, 777–784. https://doi.org/10.1016/j.jbusres.2015.07.012.
Hobday, M., 2005. Firm-level innovation models: perspectives on research in developed and developing countries. Technol. Anal. Strat. Manag. 17, 121–146. https://doi.org/10.1080/09537320500088666.
Huang, Y.-S., Hsueh, T.-L., Zheng, G.-H., 2013. Decisions on optimal adoption time for new technology. Comput. Ind. Eng. 65, 388–394. https://doi.org/10.1016/j.cie.2013.03.006.
Ilori, M.O., Irefin, I.A., 1997. Technology decision making in organisations. Technovation 17, 153–160. https://doi.org/10.1016/S0166-4972(96)00086-7.
Jarrel, T., 2017. Success Factors for Implementing Change at Scale. McKinsey & Co Presentation. Behavioral Science & Policy Association, New York.
Jones, B.D., 2003. Bounded rationality and political science: lessons from public administration and public policy. J. Publ. Adm. Res. Theor. 13, 395–412. https://doi.org/10.1093/jpart/mug028.
Kandel, E., Lazear, E.P., 1992. Peer pressure and partnerships. J. Polit. Econ. 100, 801–817. https://doi.org/10.1086/261840.
Katz, E., Lazarsfeld, P.F., 2006. Personal Influence: the Part Played by People in the Flow of Mass Communications, second ed. Transaction Publishers, New Brunswick, N.J.
Kellermanns, F.W., Walter, J., Floyd, S.W., Lechner, C., Shaw, J.C., 2011. To agree or not to agree? A meta-analytical review of strategic consensus and organizational performance. J. Bus. Res. 64, 126–133. https://doi.org/10.1016/j.jbusres.2010.02.004.
Kim, L., 1980. Organizational innovation and structure. J. Bus. Res. 8, 225–245. https://doi.org/10.1016/0148-2963(80)90012-0.
Knudsen, T., Levinthal, D.A., 2007. Two faces of search: alternative generation and alternative evaluation. Organ. Sci. 18, 39–54. https://doi.org/10.1287/orsc.1060.0216.
Kotter, J.P., Schlesinger, L.A., 1989. Choosing strategies for change. In: Asch, D., Bowman, C. (Eds.), Readings in Strategic Management. Macmillan Education UK, London, pp. 294–306. https://doi.org/10.1007/978-1-349-20317-8_21.
Kuandykov, L., Sokolov, M., 2010. Impact of social neighborhood on diffusion of innovation S-curve. Decis. Support Syst. 48, 531–535. https://doi.org/10.1016/j.dss.2009.11.003.
Lee, S., Csaszar, F.A., 2020. Cognitive and structural antecedents of innovation: a large-sample study. Strat. Sci. 5, 71–97. https://doi.org/10.1287/stsc.2020.0107.
Lewin, K., 1947. Frontiers in group dynamics: concept, method and reality in social science; social equilibria and social change. Hum. Relat. 1, 5–41. https://doi.org/10.1177/001872674700100103.
Luce, R.D., 1956. Semiorders and a theory of utility discrimination. Econometrica 24, 178. https://doi.org/10.2307/1905751.
Macy, M.W., Willer, R., 2002. From factors to actors: computational sociology and agent-based modeling. Annu. Rev. Sociol. 28, 143–166. https://doi.org/10.1146/annurev.soc.28.110601.141117.
New-product diffusion models. In: Mahajan, V., Muller, E., Wind, Y. (Eds.), 2000. International Series in Quantitative Marketing. Springer US.
Marwell, G., Oliver, P., 1993. The Critical Mass in Collective Action. Cambridge University Press.
Marwell, G., Oliver, P.E., Prahl, R., 1988. Social networks and collective action: a theory of the critical mass. III. Am. J. Sociol. 94, 502–534. https://doi.org/10.1086/229028.
Meaney, M., Pung, C., 2008. McKinsey Global Results: Creating Organizational Transformations. The McKinsey Quarterly.
Moore, C., Newman, M.E.J., 2000. Epidemics and percolation in small-world networks. Phys. Rev. E 61, 5678–5682. https://doi.org/10.1103/PhysRevE.61.5678.
Newman, M.E.J., 2002. Spread of epidemic disease on networks. Phys. Rev. E 66, 016128. https://doi.org/10.1103/PhysRevE.66.016128.
Oliver, P., Marwell, G., Teixeira, R., 1985. A theory of the critical mass. I. Interdependence, group heterogeneity, and the production of collective action. Am. J. Sociol. 91, 522–556. https://doi.org/10.1086/228313.
Pachur, T., Suter, R.S., Hertwig, R., 2017. How the twain can meet: prospect theory and models of heuristics in risky choice. Cognit. Psychol. 93, 44–73. https://doi.org/10.1016/j.cogpsych.2017.01.001.
Piderit, S.K., 2000. Rethinking resistance and recognizing ambivalence: a multidimensional view of attitudes toward an organizational change. AMR (Adv. Magn. Reson.) 25, 783–794. https://doi.org/10.5465/amr.2000.3707722.
Porras, J.I., Robertson, P.J., 1992. Organizational Development: Theory, Practice, and Research. Consulting Psychologists Press.
Raab, J., Kenis, P., 2009. Heading toward a society of networks: empirical developments and theoretical challenges. J. Manag. Inq. 18, 198–210. https://doi.org/10.1177/1056492609337493.
Rogers, E.M., 1962. Diffusion of Innovations. Free Press, New York.
Romme, A.G.L., 2004. Unanimity rule and organizational decision making: a simulation model. Organ. Sci. 15, 704–718. https://doi.org/10.1287/orsc.1040.0090.
Russell, R.D., Russell, C.J., 1992. An examination of the effects of organizational norms, organizational structure, and environmental uncertainty on entrepreneurial strategy. J. Manag. 18, 639–656. https://doi.org/10.1177/014920639201800403.
Sáenz-Royo, C., Chiclana, F., Herrera-Viedma, E., 2022. Functional representation of the intentional bounded rationality of decision-makers: a laboratory to study the decisions a priori. Mathematics 10, 739. https://doi.org/10.3390/math10050739.
Sáenz-Royo, C., Salas-Fumás, V., 2013. Learning to learn and productivity growth: evidence from a new car-assembly plant. Omega, Management science and environmental issues 41, 336–344. https://doi.org/10.1016/j.omega.2012.03.010.
Sah, R.K., Stiglitz, J.E., 1986. The architecture of economic systems: hierarchies and polyarchies. Am. Econ. Rev. 716–727.
Salas-Fumás, V., Sáenz-Royo, C., Lozano-Rojo, Á., 2016. Organisational structure and performance of consensus decisions through mutual influences: a computer simulation approach. Decis. Support Syst. 86, 61–72. https://doi.org/10.1016/j.dss.2016.03.008.
Salganik, M.J., Dodds, P.S., Watts, D.J., 2006. Experimental study of inequality and unpredictability in an artificial cultural market. Science 311, 854–856. https://doi.org/10.1126/science.1121066.
Scheibehenne, B., Pachur, T., 2015. Using Bayesian hierarchical parameter estimation to assess the generalizability of cognitive models of choice. Psychon. Bull. Rev. 22, 391–407. https://doi.org/10.3758/s13423-014-0684-4.
Schumpeter, J.A., 1934. The Theory of Economic Development: an Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle, Social Science Classics Series. Transaction Books, New Brunswick, N.J.
Seo, H., Chung, Y., Yoon, H., David, 2017. R&D cooperation and unintended innovation performance: role of appropriability regimes and sectoral characteristics. Technovation 66 (67), 28–42. https://doi.org/10.1016/j.technovation.2017.03.002.
Seshadri, S., Shapira, Z., 2003. The flow of ideas and timing of evaluation as determinants of knowledge creation. Ind. Corp. Change 12, 1099–1124. https://doi.org/10.1093/icc/12.5.1099.
Sharma, M., Sehrawat, R., 2021. Decision-making in management of technology: a literature review. Int. J. Technol. Intell. Plann. 13, 38–62. https://doi.org/10.1504/IJTIP.2021.117996.
Simon, H.A., 1947. Administrative Behavior. Free Press, New York.
Sinclair, G., Klepper, S., Cohen, W., 2000. What's experience got to do with it? Sources of cost reduction in a large specialty chemicals producer. Manag. Sci. 46, 28–45. https://doi.org/10.1287/mnsc.46.1.28.15133.
Sutton, R.S., Barto, A.G., 1998. Reinforcement Learning: an Introduction, Adaptive Computation and Machine Learning. MIT Press, Cambridge, Mass.
Tsoukas, H., Chia, R., 2002. On organizational becoming: rethinking organizational change. Organ. Sci. 13, 567–582. https://doi.org/10.1287/orsc.13.5.567.7810.
van Alstyne, M., 1997. The state of network organization: a survey in three frameworks. J. Organ. Comput. Electron. Commer. 7, 83–151. https://doi.org/10.1080/10919392.1997.9681069.
Venture Beat Staff, 2019. Why do 87% of data science projects never make it into production? VentureBeat. URL 7.2.21. https://venturebeat.com/2019/07/19/why-do-87-of-data-science-projects-never-make-it-into-production/.
Wang, C., Lu, I., Chen, C., 2008. Evaluating firm technological innovation capability under uncertainty. Technovation 28, 349–363. https://doi.org/10.1016/j.technovation.2007.10.007.
Wang, C.-H., Chin, Y.-C., Tzeng, G.-H., 2010. Mining the R&D innovation performance processes for high-tech firms based on rough set theory. Technovation 30, 447–458. https://doi.org/10.1016/j.technovation.2009.11.001.
Wang, J., Lin, W., Huang, Y.-H., 2010. A performance-oriented risk management framework for innovative R&D projects. Technovation 30, 601–611. https://doi.org/10.1016/j.technovation.2010.07.003.
Wasserman, S., Faust, Katherine, 2013. Análisis de redes sociales: métodos y aplicaciones. CIS, Madrid.
Wright, C., Sturdy, A., Wylie, N., 2012. Management innovation through standardization: consultants as standardizers of organizational practice. Res. Pol. 41, 652–662. https://doi.org/10.1016/j.respol.2011.12.004.
Yelle, L.E., 1979. The learning curve: historical review and comprehensive survey. Decis. Sci. J. 10, 302–328. https://doi.org/10.1111/j.1540-5915.1979.tb00026.x.
Zangwill, W.I., Kantor, P.B., 1998. Toward a theory of continuous improvement and the learning curve. Manag. Sci. 44, 910–920. https://doi.org/10.1287/mnsc.44.7.910.