Technovation 129 (2024) 102884

Contents lists available at ScienceDirect

Technovation

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

Reacting and recovering after an innovation failure. An agent-based approach

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ARTICLE INFO

Keywords:
Failure
Patents
Open innovation
Agent-based models

ABSTRACT

A company's growth depends not only on its achievements but also on how it can recover from failures. The study of innovation failure and learning-from-failure has gained attention over the years. Described as a complex problem, the dynamic of learning occurs as a non-linear phenomenon. Therefore, this study develops an agent-based model to examine and investigate, as a complex system, the impact on firms' performance of two main possible strategies of learning-from-failure, i.e. (1) the leveraging of the own experience and (2) the use of external resources. The findings suggest that embracing a learning-from-failure strategy in the innovation process enhances the firms' performance. In addition, the innovation intensity of the sector influences the impact of the strategy chosen. Comparing the use of internal vs external resources, the former seems to be a better strategy for enhancing the company's performance.

1. Introduction

Innovation is a rocky learning path set up with numerous challenges that may lead to failures (Forsman, 2021), i.e. in a broad sense, "each negative deviation of actual outcomes from expected ones" (Politis and Gabrielsson, 2009). Failure is not always only a negative event but it is something inevitable and useful. Studies proved that a certain number of failures is needed for an optimal innovation strategy (Guzzini et al., 2018). The failure rates of innovation processes are even higher than failures in other firms' processes and learning from them is described as a complex phenomenon (Rhaiem and Amara, 2021). Thus, between 40% and 90% of innovation projects fail mainly because of the inherent nature of innovation (Rhaiem and Amara, 2021) or the environment in which firms compete (Edmondson, 2011). For this reason, learning-from-failure is a window of wisdom for future success and it differs from learning-from-success (Magazzini et al., 2012; Edmondson, 2011). Important researchers intuitively adhere to IDEO's slogan, "Fail often in order to succeed sooner". As well, famous companies' examples confirm this claim. Amazon CEO Jeff Bezos said that "Experiments are by their very nature prone to failure. But a few big successes compensate for dozens and dozens of things that didn't work." and this was clear when the Amazon phone revenues did non overcome its costs being one of their most famous failures. However, from analysing it, they learn the importance of having a bigger picture about the users' needs and an understanding of the time to market (Taylor, 2017). The multi-billionaire James Dyson, Founder and Chairman of Dyson, went through more than five thousand prototypes before arriving at the dual cyclone bagless vacuum cleaner that is the key innovation behind his products. For him, understanding and learning from those thousands of failures was a way of forcing himself to be creative: "You don't have to bother to be creative if the first time you do something, it works," One example of this learning is embodied in a new hand-dryer technology invented while trying to set up a totally different project. A similar situation happens in Microsoft's experience. The founding duo of Paul Allen and Bill Gates wanted to use 8-bit microprocessors to help municipalities measure traffic patterns on their roads. However, they were unable to get money for the new technology. Years later, Allen says the experience confirmed that "every failure contains the seeds of your next success. It bolstered my conviction that micro-processors would soon run the same programs as larger computers but at a much lower cost. It also sparked my idea to simulate the 8008 microchip environment on a mainframe, which led to [...] the first high-level language designed to run on a microprocessor. This was the essential step toward a personal computer that anyone could use, and the keystone for the creation of

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https://doi.org/10.1016/j.technovation.2023.102884
Received 28 February 2023; Received in revised form 26 August 2023; Accepted 25 September 2023
Available online 19 October 2023

Microsoft.”.[1]

Nevertheless, firms that talk about “learning from innovation failure” are rare. This gap is mainly due to disbelieving about failures and not to a lack of commitment to learning. Companies and consultants prefer to talk about their successes and not report failures (Mueller and Shepherd, 2016; Puliga et al., 2022). Furthermore, the activities useful to effectively manage failures need context-specific strategies and to go beyond general lessons. Two main theoretical lenses can be used to study “learning-from-failure” mechanisms: the learning theory and the resource-based view (RBV) theory. The learning theory leverages the concept of capitalizing on errors describing the process as a no-linear complex system (Harkema, 2003). The application of learning theories to innovation failures helps in improving the understanding of failure also in innovation fields. In addition, the learning theory of strategic management postulated by Ginter and White (1982) posits that the firm develops skills through the interaction between employees as well as with the environment. This theoretical approach is well fitting also with the RBV (Greve, 2021), which is organized around resources that cannot be easily reproduced by competitors. The RBV helps in understanding the learning-from-failures process because of concerns about the number of resources and skills that the company can leverage to innovate and the ones that can be acquired also through failures. Also for this theory, learning can essentially happen either from own experience and resources which represent a key source of path dependence and hence create unique competencies, i.e. the skills embodied in employees, or from external actors which consist of transferring resources to create less imitable innovations, i.e. from the interactions with the environment. Namely, the employment of one own experience is important to both theories, but also the use of external resources, illustrate how companies may build a competitive advantage through learning from a failure by opening up their innovation process, i.e. adopting an Open Innovation strategy (OI) (Christensen, 2006; Teece, 2007; West and Bogers, 2017; March, 1991). To date, despite the high failure rate, there is a paucity of research that analyses innovation failures (Maslach, 2016), even more as a complex system, and how companies can learn from them in order to reinforce positive outcomes while limiting the negative consequences of failure. In this regard, in this paper, an agent-based model (ABM) will be developed to understand how the use of “internal”, “external” or the combination of both “internal” and “external” resources can enhance firms’ performance when reacting to a failure. It will use the lens of the learning-complex theory and the RBV theory that allow to better understand how firms can turn their failure experiences into learning paths also according to which kind of resources is leveraged and the competitive environment to which they belong, e.g. the level of innovation of the company’s sector. ABM is particularly fitting because learning-from-failure is a process composed of different and multiple steps that define a complex and nonlinear process (Edmondson, 2011) and it is acknowledged for being among the most appropriate methods to cope with complexity. In addition, ABM are a promising method for critically assessing prior theories, already developed, for example, with case studies in order to get depth insights that only modelling can offer without high costs (Miller, 2015; Fioretti, 2013). Furthermore, these models allow producing important knowledge advances on the issues and on the theories they have critically addressed (Gómez-Cruz et al., 2017). Indeed, an ABM exhibits high learning and as suggested by Fioretti (2013) “the very process of constructing the model may be at least as important as the outputs that the model yields” (p. 230). Compared to other modelling techniques, ABM is particularly useful when path dependence is an important element of the system and agents can adapt their behaviours as happens in innovation learning-from-failures (Castellani et al., 2019).

The ABM simulations presented in this paper show that embracing a learning-from-failure strategy enhances firms’ performance more than not having any strategy. Comparing the use of internal vs external resources, the former seems to be a better strategy for enhancing the company’s performance and not always combining the two is convenient in terms of performance. In addition, the paper compares the strategies in contexts with different levels of innovation and different rates of innovation failures allowing us to study how the behaviour can change in different contexts. These results contribute to the theory by analysing learning-from-failures in innovation with a complex lens and by using a novel approach to address such literature gaps, i.e. ABMs.

The paper is structured as follows. In section 2, the theoretical background regarding the possible strategies for learning-from-failures and how complex innovation systems have been studied with ABM. Then, in section 3, the ABM is described and then in section 4, the experiments run are presented and the findings introduced. Then, in section 5, they have been discussed and implications have been provided. Finally, in section 6 conclusions and further developments are presented.

2. Literature review

2.1. *Strategies for learning from innovation failures*

Learning from innovation failure can be recognized as a major input to the future development of successful innovations. Learning implies that the companies adopt strategies triggered when a failure occurs which leads to different decision-making processes and possible investment. This allows examining past mistakes, the roots of failure may be identified in order to offer solutions and improve current and future results. From this perspective, learning-from-failures enhances the knowledge held by managers and employees and it is not simply the correction of errors (Carmeli et al., 2012). In this context, companies belong to an innovation system/ecosystem where actors, artefacts, and activities are linked together by means of relations that evolve during the flow of time (Phillips and Ritala, 2019; Granstrand and Holgersson, 2020) and from which they can learn.

According to the RBV and to the searching strategy literature (Cassiman and Veugelers, 2006; Kerr et al., 2006; Fabrizio, 2009) two main clusters of strategies can be adopted in order to develop rare and valuable resources: internal investments (Cassiman and Veugelers, 2006) and external search (West and Bogers, 2014). According to a first cluster of strategies, companies can use internal specialized competencies to understand failures and learn from them in order to create a competitive advantage over their competitors leading to superior performance (Lockett et al., 2009). Companies invest in understanding the failure and try to change behaviors in order to turn failure into success (Morais-Storz et al., 2020; Bong and Park, 2021). Indeed, firms’ failures affect managers’ choices in terms of innovation investment and until certain levels, higher investments are likely to be triggered (Bong and Park, 2021). This is verified by the fact that even in a situation of crisis and failure, the world’s top innovators increase their R&D investment in order to enhance innovation. The exploration in general and the exploration of failures is typically embedded in the kind of commitment that firms’ innovation strategies show toward formal R&D investment. Indeed, firms’ investment in R&D nurtures expertise and creates new opportunities for the building of in-house competencies and also to understand the causes of failure and develop new successful products and processes (D’Este et al., 2018). Indeed, as stated by the pioneering work of Penrose and Penrose (2009), the way managers dispose of resources and investments will influence the advance of firms’ innovation and the firm’s performance. In this way, companies create knowledge dynamics in terms of sensemaking mechanisms of problem formulation post-failure. Teams reformulate the problem representation and go retrospectively to find innovative solutions. Specifically, the organization advances through individuals who learn. A series of routines, practices, and adaptive capacities can be proposed by the company to influence the learning activities (García-Morales et al., 2009).

[1] https://www.newsweek.com/my-favorite-mistake-paul-allen-66489.

According to a second cluster of strategies, companies can shift the boundaries conditional upon their current resource set. Companies can leverage their network and use external sources to cope with such failures and learn from them. RBV research explains how firms build competitive advantage by means of OI strategies that span organizational boundaries and allow them to enlarge their resource base (Vanhaverbeke and Chesbrough, 2014). Indeed, complementary resources allow a firm to build an advantage by lowering the rarity and value of a once-scarce resource (West and Bogers, 2017). A large share of the literature shows that collaboration in innovation projects enhances the firms' performance (Guzzini et al., 2018) and the literature on the use of the knowledge and technology network is widely diffused. In fact, companies that belong to a system represent the components whereas the relationships exchanged among them the knowledge or the technology transferred. According to Najafi-Tavani et al. (2018), the system/innovation networks enhance the firm's performance when its level of internal capabilities is high. On the way around, networks can be seen as a waste of resources when companies lack internal capabilities to capitalize on external resources (Najafi-Tavani et al., 2018). Failure in innovation projects may induce companies to collaborate later in order to overtake the issues experienced in previous projects. As proved by Guzzini et al. (2018), the occurrence of innovation failures positively affects the probability of collaborating in later periods. Probably, companies establish new collaborations since they are not capable of completely anticipating the issues emerging when implementing and developing innovation projects. The failure of these projects may depend on the lack of resources and competencies, which may induce firms to consider innovation collaborations as a possible way to fill these gaps (Guzzini et al., 2018).

2.2. Studying complex innovation systems with agent-based models

According to more recent learning theories, knowledge can be transferred but learning is an individual process. This process is not linear and complex adaptive systems allow grasping such non-linearity and map dynamic behaviors (Harkema, 2003). Indeed, each agent, i.e. company, contains a part of organizational rules, and a part of individual elements. Agents are the decision-making units of an innovation project, and they can choose to learn and mitigate the failure, they can select a specific learning strategy and consequently determine the evolution of the process. In the system, different agents interact and mutually affect each other within an innovation ecosystem. Consequently, agents' strategies and interactions lead to non-linear, dynamic behavior and self-organization. Marginal changes and variations can also generate large unexpected and unpredictable effects that exponentially grow in magnitude over time. Small changes can trigger larger changes later on, generate radical changes, and create a dynamic of events that escalate in time (Harkema, 2003). Specifically, agents can choose different strategies to learn from innovation failures (Bong and Park, 2022). In this context, ABMs appear particularly useful to model the learning process arising from failures. ABMs adopt a realist approach in which observable actions are modeled with a detailed representation of agents that live in complex environments (An et al., 2021). Thus, ABMs allow modelling individuals' uniqueness and their interactions among themselves and/or the environment(s). Moreover, agents can live in time-varying and heterogeneous environment(s), by adapting their behaviours to current or also future states of themselves and their environment in order to pursue a certain objective. Hence ABMs allow for studying a wider range of behavioral phenomena or processes and addressing many empirical and theoretical complex problems (Arthur, 1999). ABMs can simulate potential interventions such as different learning strategies, with results used to inform decisions (Ponta et al., 2023). In this way, ABM can explore (without high costs) the capacity of different interventions to drive complex phenomena in a more effective direction (Barbrook-Johnson et al., 2020). ABMs have been increasingly used in management literature over the past years, producing advances in the knowledge of the issues and theories they have critically addressed (An et al., 2021). Adopting the ABM approach allows scrutinizing critically previous theories and conjectures and acts as a virtual laboratory in which modellers can explore the evolving interactions among various agents and mimic different strategies and interventions. Acknowledged the importance of modeling and the potential of the ABM approach, to date the ABMs used to explore insights and test results emerging from case studies and/or surveys in terms of learning-from-failures are rare.

The existing works in the innovation management field mainly focus on collaborative networks, on the role of the network in fostering or slowing down innovation diffusion or on the exploration/exploitation dilemma (Kiesling et al., 2012; March, 1991). Collaborative networks have been used by Ponta et al. (2023) to see the impact of different cooperative strategies on firms' performance. Mood et al. (2023) analysed the problems and challenges of collaborations, Ahrweiler et al. (2011) see the role of universities in innovation networks and Heshmati and Lenz-Cesar (2013) depict the dynamic processes of cooperative innovation and see companies' reactions to different policies. Regarding network diffusion, for example, Hua et al. (2022) studied how the network density affects the efficiency of innovation networks, Mueller and Ramkumar (2023) looked at the role of negative links in the diffusion of innovation, Dosi et al. (2023) studied the patent system and Zapata-Roldan and Sheikh (2020) the design management of new product development. Other important ABM works regard organizational learning according to which a trade-off between exploration and exploitation exists. Since the work of March (1991) and subsequent revisits (Miller et al., 2006; Wilden et al., 2018) the exploration of new possibilities and the exploitation of old ones has been a main question.

3. The model

In order to investigate the research question described above, an agent-based innovation model and simulator have been developed. In particular, the baseline of the Patent Agent-based Innovation Model has been enriched including new features about the company's strategies in case of innovation failure (Ponta et al., 2023). The model is characterized by heterogeneous firms whose final goal is to increase innovation and economic performance. At the beginning of the simulations, each firm k is characterized by a different percentage α_k of profit invested in R&D research. The percentage α_k varies during the simulation according to the specific strategy adopted by firm k. All the R&D investments are finalized to patent. In addition, a firm is characterized by the profit U_k, and its size S_k, which depends proportionally on the number of employees. If the profit increases, new employees are hired and the size increases, whereas if the profit decreases some employees are fired and, consequently, the size decreases. In formulas,

$$\Delta N_k(t) = \left\lfloor \frac{U_k(t)}{\gamma} \right\rfloor - N_k(t-1) \tag{1}$$

where γ is the average profit per employee and N_k is the number of employees of firm k. At each iteration step t each firm k invests a fraction $m_k(t) = \alpha_k U_k(t-1)$ of the profit in R&D finalized to patent. The probability of firm k filing for a patent at time t depends on the cumulated R&D investments of firm k, M_k since the last patent issued and on the environment. In formulas:

$$\rho_k(t) = \frac{1}{1 + \eta M_k(t)} \tag{2}$$

where η is the sector innovation intensity. Moreover, firms are organized in networks. Thus, firms, that do not have enough cumulated R&D investments to file for a patent alone can ask the connected firms if copatenting is possible. At the beginning of the simulation, all the firms are organized according to a regular direct random graph, which means that at the beginning of the simulation, each firm has the same number of output connections, i.e. it has the same outdegree node (Erdős and

Rényi, 1960). It is worth noting that the graph is unidirectional in order to mimic the decision-making perspective. Thus, the probability of copatenting is

$$\rho_{ki}(t) = \frac{1}{1 + \eta(M_k(t) + M_i(t))} \tag{3}$$

i.e. firm k and i put together their cumulated R&D investments.

If a patent or a copatent is not possible, firms can extend a patent issued at time step t - 1 in other countries. See (Ponta et al., 2023) for further details.

A patent or a copatent is featured by a fixed and a variable cost. The fixed cost F of a patent or copatent p represents taxes whereas the variable cost C_p is equal to the R&D investments, i.e. $C_k^p = M_k$ in case of patent or $C_k^p = M_k + M_i$ in case of copatent, respectively. The value of a patent or a copatent is evaluated as a function of the total costs of a patent or a copatent as:

$$Vk^p(t) = \mu(F + C_k^p) \tag{4}$$

Where μ is a positive coefficient randomly drawn from a uniform distribution. The failure of a patent or copatent is here modeled considering $0 \leq \mu \leq 1$, i.e. a patent or a copatent whose value is smaller than or equal to the cost incurred. It is worth noting that the revenues are equal to the patent value or proportional according to the amount of investments in the case of patent or copatent, respectively. Moreover, the patents and copatents remunerate two years after the patents or copatents are issued in order to mimic the 18-month delay. Finally, at the end of the time step, the profit of each firm is updated by adding the revenues of new patents or copatents issued or extended and subtracting the new investments in R&D and the costs of new patents or copatents and extensions. See Ponta et al. (2023) for further details.

3.1. Firm strategy in case of innovation failure

In case of innovation failure, here modeled with a patent or a copatent that remunerate less than issue costs, firms can adopt different strategies that, as illustrated in Section 2, can be summarized as "Levaraging internal resources (LIR)" and "Levaraging OI (LOI)". In the model, the LIR strategy can be modeled as an increase of investment in R&D after an innovation failure (Bong and Park, 2021). Thus, if a patent p issued by firm k at time step $t-1$ was a failure, firm k, at time step t will increase α_k of ϵ. The LOI strategy is modeled as a change in the firm's network after an innovation failure (Guzzini et al., 2018). Thus, if a patent or a copatent p issued by firm k at time step $t-1$ was a failure, firm k modifies its connections adding a new connection with the firm with the largest patent successful rate. Figs. 1 and 2 show the main steps of the two strategies.

Fig. 1 shows that, after the initialization of the model, at each time step t each firm k checks if a patent issued is a successful innovation or not. If yes, the firm k continues with the previous strategy, if no the firm k increases the investments in R&D, i.e. $\alpha_k(t+1) = \alpha_k(t) + \epsilon$.

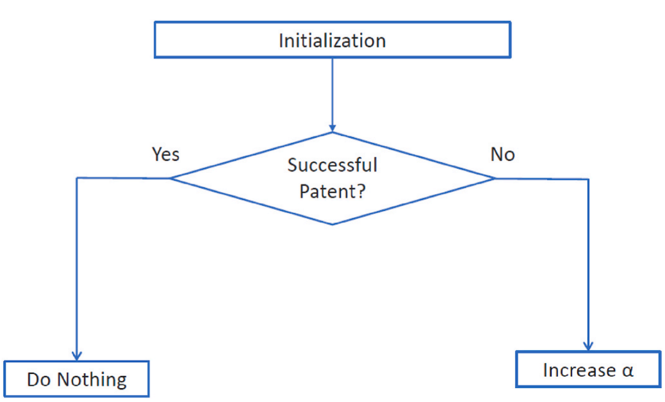


Fig. 1. Firm LIR strategy.

Fig. 2 shows that, after the initialization of the model, at each time step t each firm k checks if a patent or a copatent issued is a successful innovation or not. If yes, the firm k continues with the previous strategy, whereas if no the firm adds a new connection with the firm with the largest successful innovation rate. Moreover, in case of copatenting failure, the firm also deletes the connection with the firm with whom the copatenting was a failure.

3.2. Firms' network evolution

As said in subsection 3.1, firms are organized according to a directed random graph, i.e. the links are unidirectional and thus, the node's indegree and outdegree can be defined (Erdős and Rényi, 1960). At the beginning of the simulation, all the firms have the same node's outdegree. During the simulation, the network evolves in a different way according to the specific strategy, i.e. no strategy after a failure, LIR strategy and LOI strategy, adopted by firms after an innovation failure. If firms adopt no strategy or a LIR strategy, the node's outdegree of each firm changes in a way directly proportional to the firm's size, i.e., it increases if the firm's size increases and decreases if the firm's size decreases. The firm's size depends on its turnover (Friedland, 1957). See Ponta et al. (2023) for further details. If firms adopt the LOI strategy, at each time step t each firm k checks if a patent or a copatent issued is a successful innovation or not. If yes, no change in the network will be made, whereas if no the firm k adds a new connection with firm i, i.e. the firm with the largest successful innovation rate. Moreover, in case of copatenting failure between firm k and j, the firm k deletes the connection with the firm j, i.e. the connection with the firm with whom the copatenting was a failure and creates a new connection with firm i, i.e. the firm with the largest successful innovation rate.

3.3. Firm's performance

At each iteration step, the economic and innovation performance of firm k is updated. The economic performance is approximated with the profit, whereas the innovation performance with the Innovation Patent Index (IPI) (Goldstein et al., 2001; Ponta et al., 2021). Profit is evaluated as revenues minus costs as described in Section 3, whereas IPI is a multidimensional measure of innovation performance, based on secondary data, composed of five dimensions defined by using different machine learning algorithms (Ponta et al., 2022). For each dimension, an indicator has been defined: (a) Efficiency: the number of patents normalized with respect to the number of employees; (b) Diversification: the number of IP classes; (c) Quality: the number of backward citations; (d) Internationalization: the number of extensions; (e) Time: the number of months between the publication date of the youngest and the oldest patent of the family. Thus, IPI is a more complete measure of innovation performance as it considers not only the classical measure of the number of patents but also other characteristics of patents (Dziallas and Blind, 2019).

4. Computational experiments

All the computational experiments performed make reference to the enriched version of PABIM described in Section 3 with 50 firms. Each firm is initially endowed by a fixed quantity of cash, equal among the firms, finalized to patent. Moreover, each firm is characterized by the percentage α that ranges between 2 and 17 at the beginning. The initial value of the main variables of the model are summarized in Table 1. Furthermore, the effects of the different strategies described in Section 3 are investigated in two different types of sectors, i.e. sectors with high rate of failure, such as healthcare and with small rate of failure, like the agro-industry (Dhamvithee et al., 2005). The results are presented by means of boxplots. Each boxplot shows the distribution of the time

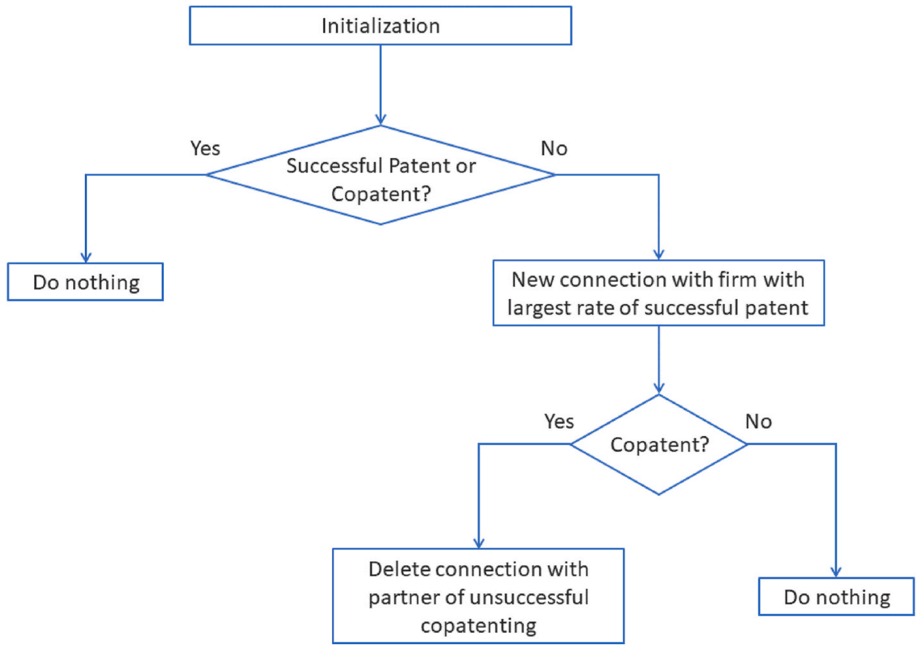


Fig. 2. Firm LOI strategy.

averages of the firms' performance over a twenty-year time interval, regarding the fifty simulations initialized with different seeds (Bertani et al., 2021). Table 2 summarizes all the scenarios considered in the analysis.

Table 2
Scenario description.

Scenario	Description	Color
i	Firms do no adopt any strategy after a failure	Blue
ii	Firms adopt LIR strategy	Azure
iii	Firms adopt LOI strategy	Red
iv	Firms adopt both LIR and LOI strategy	Magenta

4.1. Results

As suggested by the literature, the main goal is to understand the impact of different failure learning strategies on firms' performance with respect to different values of the sector innovation intensity and to different rates of failure. The firm performance, as described in Section 3, has been investigated with the economic and innovation performance, approximated with the profit and the Innovation Patent Index (IPI), respectively (Goldstein et al., 2001; Ponta et al., 2021). Both the economic and innovation performance have been studied in two cases: (a) a sector with a high rate of failure, and (b) a sector with a low rate of failure. Table 3 reports the two cases and the specific simulation parameter values. In terms of economic performance, Fig. 3 shows the distribution of economic performance approximated with the profit for different values of the sector innovation intensity, η in a sector with high (a) and low (b) rate of failure, respectively. Healthcare is an example of a sector with low rates of innovation failures whilst consumer goods or chemicals are industries where the rates of innovation failures are higher (Rutkowski et al., 2022). The blue boxplots correspond to scenario (i), the red boxplots to scenario (ii), the azure boxplots to scenario (iii) and the magenta boxplots to scenario (iv)). It is worth noting that in scenarios (ii) and (iv) five boxplots are plotted. This is because when firms adopt the LIR strategy they increase the investments in R&D after an innovation failure and in the model five different values of ϵ are considered, i.e. $\epsilon = 0.1$, $\epsilon = 0.5$, $\epsilon = 1.0$, $\epsilon = 2.0$,$\epsilon = 5.0$.

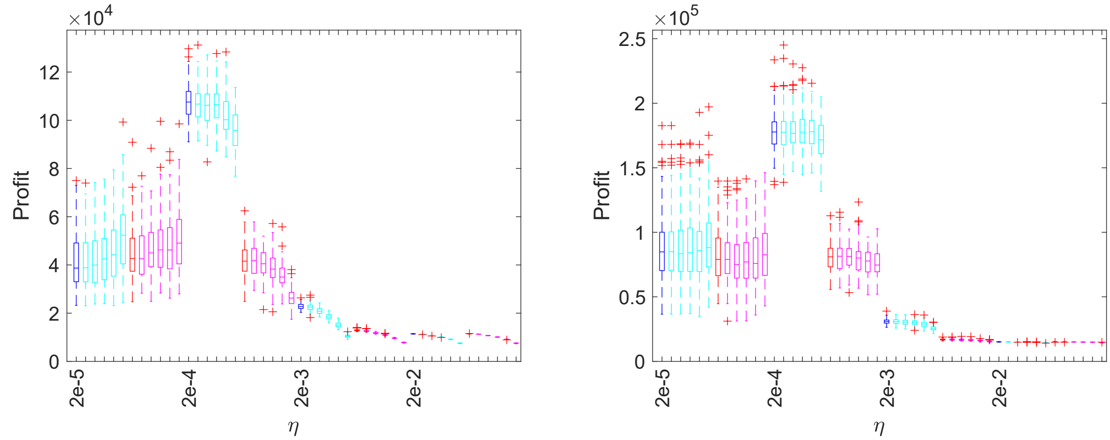
Table 1
Simulations parameters.

Variable Description	Value	Source
years	20	experiment design
number firms	50	
initial profit	20000	
sector innovation intensity	2×10^{-5} to 2×10^{-2}	
maximum number of Countries	38	
maximum number of technological domain	50	
number of initial output connection	1	
initial % of profit invested in R&D	[2–17]	panel of experts
multiplier range case a	[0.7–1.1]	
multiplier range case b	[0.5–2]	
increment % of profit invested in R&D	[0.1–5.0]	
coefficient for management cost	0.9	
patent extension cost	350	
patent application fixed cost	500	
average profit per employee	500	

Table 3
Cases description.

Cases	Description	Simulation Parameters	
		Variable	Value
a	Sector with high rate of failure	multiplier	0.9
		range	0.4
b	Sector with low rate of failure	multiplier	1.25
		range	1.5

Fig. 3(a) shows the effects of LIR, LOI, and the combination of strategies on economic performance, i.e. profit in sectors with a high rate of failure. For low values of η, the profit in scenario (iv) is higher than in (i), (ii), and (iii), meaning that if the sector innovation intensity is very low, firms, which adopt both an LIR and LOI strategy achieve better economic performance. Moreover, the larger ϵ the larger the economic performance. For medium values of η, the profit in scenarios (i) and (ii) is larger than in (iii) and (iv), meaning that if the sector innovation intensity is medium and large the LIR strategy or no specific strategy leads to larger economic performance. For large values of η, the profit in



(a) (b)

Fig. 3. Distribution of economic performance approximated with profit in a sector with high (a) and low (b) rate of failure, respectively. The blue boxplots correspond to scenario (i), the azure boxplots to scenario (ii), the red boxplots to scenario (iii) and the magenta boxplots to scenario (iv)). In scenarios (ii) and (iv) five boxplots are plotted. When firms adopt the LIR strategy five different values of ϵ are considered, i.e. $\epsilon = 0.1$, $\epsilon = 0.5$, $\epsilon = 1.0$,$\epsilon = 2.0$,$\epsilon = 5.0$.

scenarios (iii) and (iv) is larger than in (i) and (ii) meaning that the LOI strategy and both LIR and LOI strategy help firms to achieve better economic performance. Fig. 3(b) shows the effects of LIR, LOI, and both strategies on economic performance, i.e. profit in sectors with a low rate of failure. For low and large values of η, both no strategy nor LIR and LOI strategies have the same effects on the economic performance, in fact, the four scenarios show that the different strategies have the same behavior. For medium values of η, the LIR strategy and no strategy have a better impact on the profit.

Figs. 4–8 exhibit the five dimensions of innovation performance measured by means of the IPI, i.e. efficiency, diversification, quality, internationalization, and time.

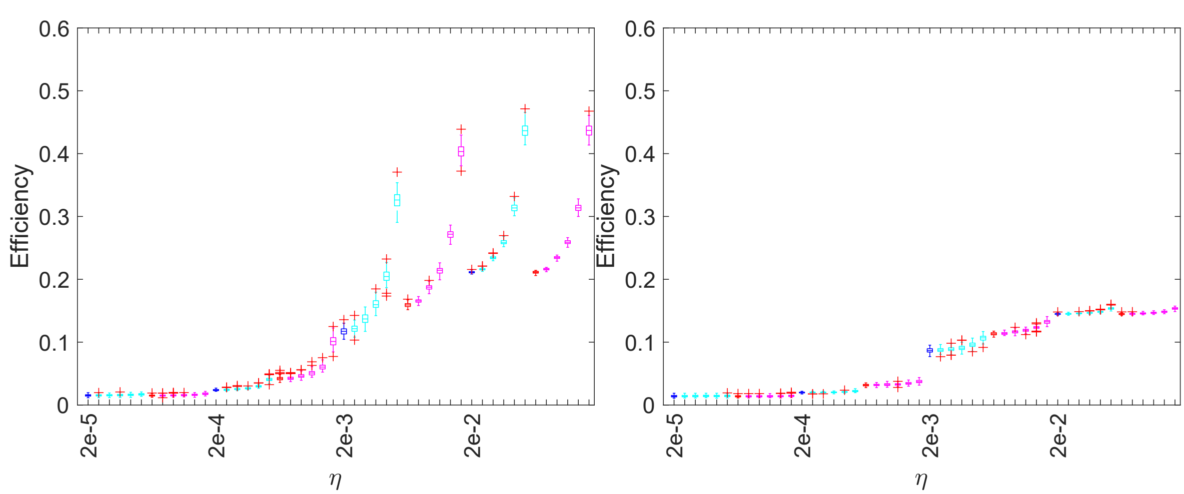
Fig. 4 shows the efficiency dimension that is evaluated as the normalized number of patents filed by firms. Fig. 4(a) shows the efficiency dimension in the case of sectors with a high rate of failure.

For low values of η, efficiency is larger in scenarios (ii), (iii), and (iv), whereas for medium and large values of η, efficiency is larger in scenario (iv), i.e. when firms adopt both LIR and LOI strategy. Thus, concerning the efficiency dimension, firms, in order to improve their innovation performance, have to implement a strategy to react to a failure and the winning strategy is a mix between LIR and LOI. This result is also confirmed in sectors with a low failure rate as shown in Fig. 4(b).

The diversification is exhibited in Fig. 5. In both cases, sectors with a high rate of failure Fig. 5(a) and low rate of failure Fig. 5(b), respectively, for low and medium values of η the diversification dimension is larger in scenarios (iii) and (iv) meaning that the LOI strategy and the mix of LOI and LIR strategy bring to a better innovation performance. For large values of η, the diversification dimension is very similar in all scenarios.

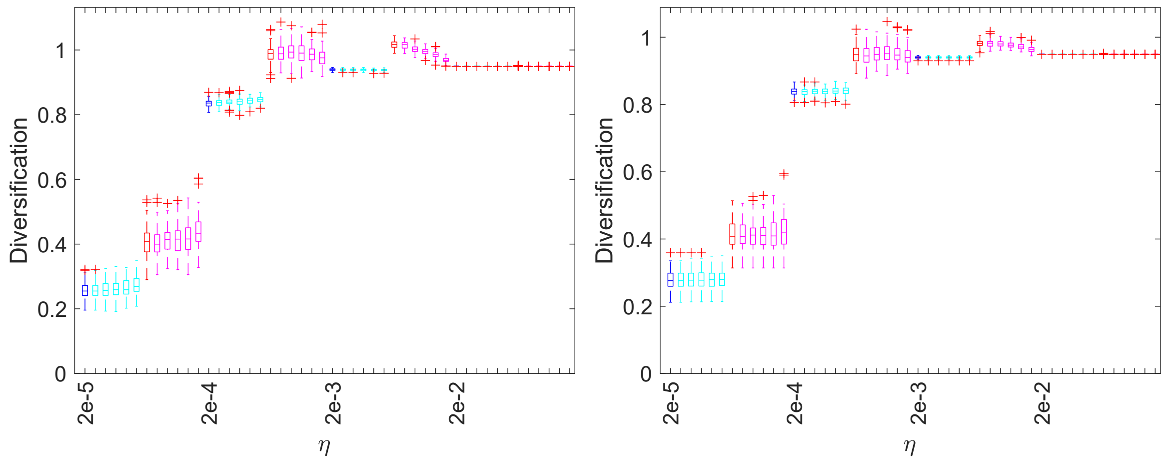
Concerning the quality, as shown in Fig. 6, in both cases, high and low rates of failure, for low values of the sector innovation intensity, η, the quality is higher in scenario (iii) and (iv), whereas for middle values the quality is higher in scenarios (ii) and (iv), and for large values of η quality is large in scenario (iii) and (iv) and for very large values quality all scenarios have the same behavior.

Moreover, the internationalization and time dimensions are exhibited in Figs. 7 and 8, respectively. In both cases, high and low rates of failure, for small η these IPI dimensions are larger in scenarios (iii) and



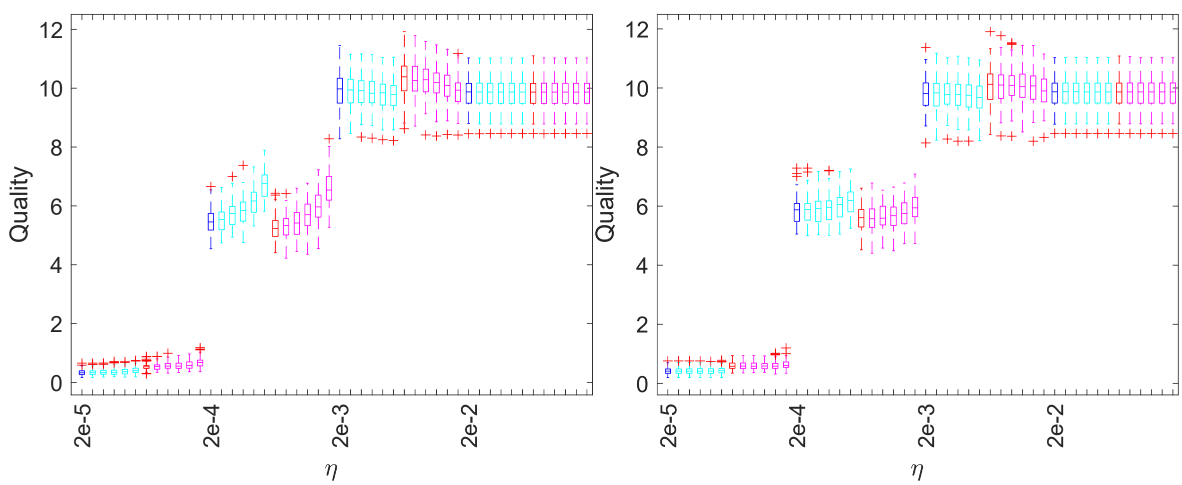
(a) (b)

Fig. 4. Distribution of the efficiency, one dimension of innovation performance approximated with IPI in a sector with high (a) and low (b) rate of failure, respectively. The blue boxplots correspond to scenario (i), the azure boxplots to scenario (ii), the red boxplots to scenario (iii), and the magenta boxplots to scenario (iv)). In scenarios (ii) and (iv) five boxplots are plotted. When firms adopt the LIR strategy five different values of ϵ are considered, i.e. $\epsilon = 0.1$, $\epsilon = 0.5$, $\epsilon = 1.0$,$\epsilon = 2.0$,$\epsilon = 5.0$.



(a) (b)

Fig. 5. Distribution of the diversification, one dimension of innovation performance approximated with IPI in a sector with high (a) and low (b) rate of failure, respectively. The blue boxplots correspond to scenario (i), the azure boxplots to scenario (ii), the red boxplots to scenario (iii) and the magenta boxplots to scenario (iv)). In scenarios (ii) and (iv) five boxplots are plotted. When firms adopt the LIR strategy five different values of ϵ are considered, i.e. $\epsilon = 0.1$, $\epsilon = 0.5$, $\epsilon = 1.0$,$\epsilon = 2.0$,$\epsilon = 5.0$.



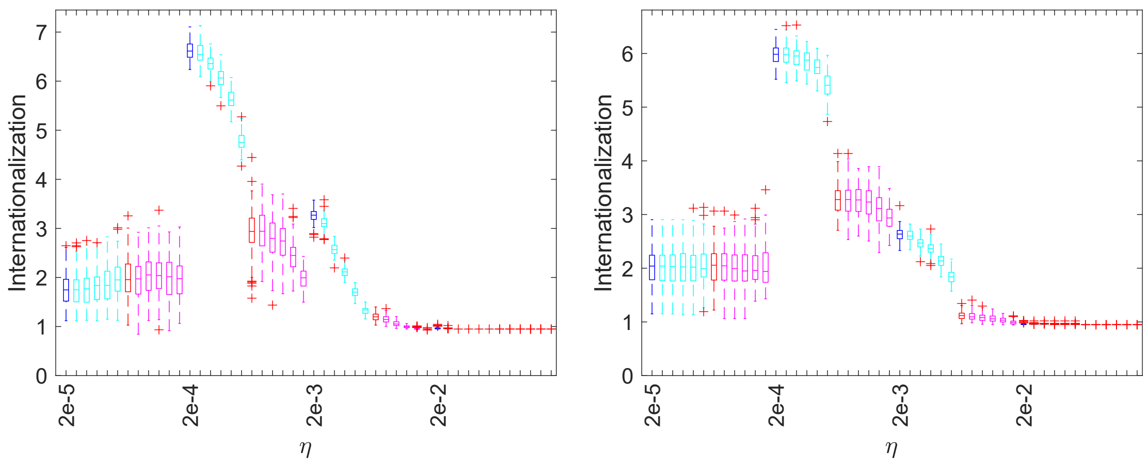
(a) (b)

Fig. 6. Distribution of the quality, one dimension of innovation performance approximated with IPI in a sector with high (a) and low (b) rate of failure, respectively. The blue boxplots correspond to scenario (i), the azure boxplots to scenario (ii), the red boxplots to scenario (iii), and the magenta boxplots to scenario (iv)). In scenarios (ii) and (iv) five boxplots are plotted. When firms adopt the LIR strategy five different values of ϵ are considered, i.e. $\epsilon = 0.1$, $\epsilon = 0.5$, $\epsilon = 1.0$,$\epsilon = 2.0$,$\epsilon = 5.0$.

(iv) than in (i) and (ii). Instead for medium η no specific strategy seems useful to improve these dimensions. For large η all the scenarios seem to behave in the same way.

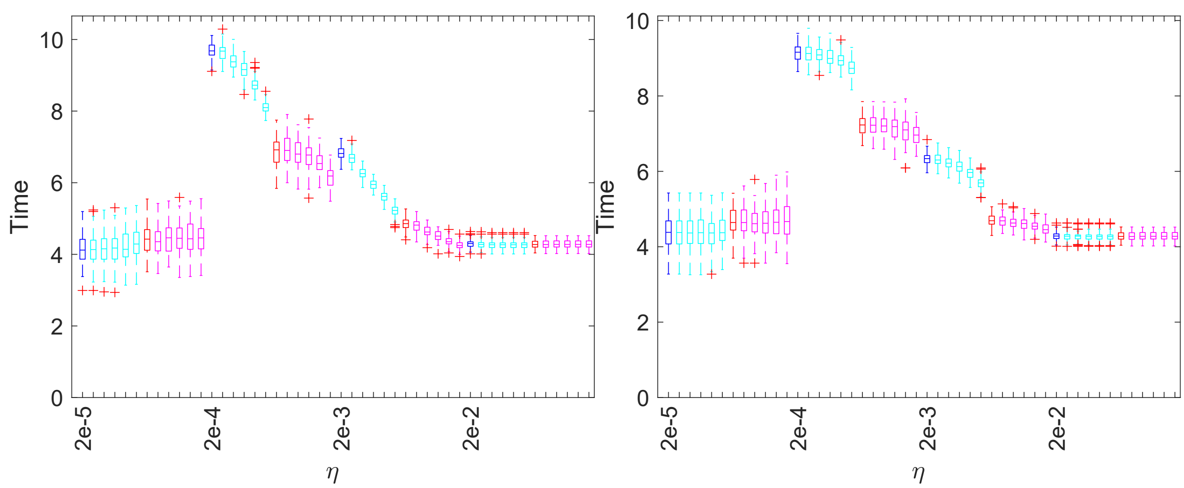
5. Discussion

Decreasing the likelihood of failure is a company's daunting task (Åstebro and Michela, 2005) and learning-from-failures is probably the most promising way to take advantage of unsuccessful innovations (Rhaiem and Amara, 2021). However, the role of failure and the set up of possible failure learning strategies are under investigated because of a lack of information about unsuccessful cases (Puliga et al., 2022; Morais-Storz et al., 2020). Learning-from-failure is a complex problem, that highly depends on the context (Harkema, 2003; Rhaiem and Amara, 2021) and most of the studies have approached it using traditional and linear systems. For this reason, the use of an ABM provides the first relevant contribution to both theory and methodology. The study helps to understand the different outcomes of learning from innovation failures also looking at contexts and outcomes. Indeed, the model allows for analyzing the impact of the learning strategies in sectors with different innovation intensities and looking at different outcomes in terms of innovation and economic performance. This extends the current literature that has mainly used qualitative approaches without quantifying the results and not characterizing the differences among companies' sectors (Bong and Park, 2021). The study supports the idea that different contexts should implement different learning strategies. Results show that the innovation intensity of the sector in which the company operates highly influences economic and innovation performance generated from different learning strategies (Edmondson, 2011). It is worth noting that the absence of a learning strategy is not fruitful in most cases. Finding some solutions when an innovation failure occurs is a winning strategy for companies because effective organizational learning helps organizations to discover uncertainties, which are difficult to predict in advance (Morais-Storz et al., 2020). This finding confirms largely the



(a) (b)

Fig. 7. Distribution of the internationalization, one dimension of innovation performance approximated with IPI in a sector with high (a) and low (b) rate of failure, respectively. The blue boxplots correspond to scenario (i), the azure boxplots to scenario (ii), the red boxplots to scenario (iii), and the magenta boxplots to scenario (iv)). In scenarios (ii) and (iv) five boxplots are plotted. When firms adopt the LIR strategy five different values of ϵ are considered, i.e. $\epsilon = 0.1$, $\epsilon = 0.5$, $\epsilon = 1.0$,$\epsilon = 2.0$,$\epsilon = 5.0$.



(a) (b)

Fig. 8. Distribution of the time, one dimension of innovation performance approximated with IPI in a sector with high (a) and low (b) rate of failure, respectively. The blue boxplots correspond to scenario (i), the azure boxplots to scenario (ii), the red boxplots to scenario (iii), and the magenta boxplots to scenario (iv)). In scenarios (ii) and (iv) five boxplots are plotted. When firms adopt the LIR strategy five different values of ϵ are considered, i.e. $\epsilon = 0.1$, $\epsilon = 0.5$, $\epsilon = 1.0$,$\epsilon = 2.0$,$\epsilon = 5.0$.

existing theory according to which framing a learning strategy is far better than not learning at all (Magazzini et al., 2012; Edmondson, 2011), also in cases with low numbers of failures. This is even truer in sectors with low innovation intensity, in which adopting a learning strategy may be particularly helpful because of the limited number of innovations and consequently, a single error may hinder the company's capacity to profit in its business. Instead, when the innovation intensity of a sector increases the adoption of learning strategies has a lower impact on performance probably because there is already a sort of continuous trial-error-learn in the innovation process itself (Young, 2009). It can be supposed that an error in low innovation intensity sectors has a higher impact on companies' performances compared to sectors where innovations are more frequent and thereby the weight of an error is marginal.

Comparing the use of internal versus external resources as failure learning strategies, in most cases, the former seems a more worthwhile strategy than the latter. As suggested by the RBV, investing in companies' own resources allows the development of critical competencies that could not be immediately replicated by others. This finding goes in the direction of Laursen and Salter (2006) according to which it is not the number of partners but the quality of the collaboration that influences the results, particularly the economic ones. Furthermore, often the amount of R&D to be invested in learning-from-failure reaches a maximum, meaning that for the company is not convenient to invest limitlessly but it has to balance the number of resources invested with respect to the results that can be obtained. It seems more important that the company dedicates a part of its budget to solve the failure and not the amount per se. Differently, investing a high amount of resources may have drawbacks because money could not be directed in an efficient way for understanding the roots of failure and could generate higher costs for the company. The use of internal resources is particularly relevant in sectors with low innovation intensity. Mainly for companies belonging to these sectors, the profit as well as the efficiency and the quality of innovation increase when the company invests internal resources to learn from failures. Instead, it would be better to leverage external resources because this allows working in different sectors and probably using the innovation in other contexts (Guzzini et al., 2018). The combination of the two strategies is not always the most convenient approach to be implemented, probably because of the costs and the complexity of management. Indeed, on one side, companies have to invest more resources and work internally to understand the problem, on the other they have to search for new partners to solve previous failures. These results confirm studies that see also a dark side of OI due to its complexity in terms of management (Stefan et al., 2022).

Consequently, the theoretical implications are twofold. First, the results contribute to the learning-from-failures research stream by adopting the RBV and merging it with complex theories as sought by Wilden et al. (2018). The study represents one of the first attempts to analyse learning-from-failures in innovation with a complex lens although it is widely proven that learning is a complex and not linear phenomenon. In particular, the study contributes to the theory by clarifying which strategy can be more useful in terms of learning. On one side, it confirms existing theory about the usefulness of learning-from-failures, but it also enriches it by modelling different interventions/strategies and how the combination of them can behave. This finding also opens up to consider more strategies that could be adopted to learn from failures. For example, the search strategy stream of literature that allows identifying the locus from where catching the new knowledge, i.e. internal or external, could be integrated with the exploration-exploitation innovation forms. Thus, this study can also enrich the literature discourse on exploration and exploitation strategies (March, 1991) and then integrate it with the RBV (Wilden et al., 2018). Second, the contribution is from a methodological point of view. The use of an ABM allows avoiding classical linear or qualitative relationships that on one side do not map the dynamics of the problem and on the other side do not allow taking out general conclusions.

The findings of the study lead to several implications for managers and innovation network designers. Managers should think about how to treat the failures and the proposed model allows them to "play" with different contexts and see different results in terms of performance. Managers, particularly the ones working in low-intensity sectors, must be aware that having a learning strategy to trigger when a failure occurs is more fruitful than doing nothing. Nevertheless, companies should not invest limitless in learning strategies, for example, also combining internal or external resources, but should focus their effort also depending on the kind of performance that they want to enhance and the level of internal know-how (Najafi-Tavani et al., 2018). Network developers should think about the network structure by looking at connections that can be useful also for learning-from-failures and develop those connections that can be helpful for companies in order to explore the best possible ways to learn from failure.

6. Conclusions, limitations and future research

This paper extends the theory about learning-from-failures and complements conventional approaches to failures literature by using complexity theory to model companies' behavior. In this study, an ABM has been developed to investigate the impact that different failure learning strategies may have on the rise of economic and innovation performance. Specifically, the model seeks to understand the role that a decision-maker can play when working with failure and trying to recover from it by searching and investing in internal and/or external resources. The study is not without limitations that open to future research. The model is a simplification of reality and more nuances in terms of strategy or firms' characteristics can be implemented. In terms of strategies, future research can investigate how LIR and LOI strategies actually support exploration and exploitation processes and how these impact firms' performance. In terms of performance, other details of the economic results can be monitored and it can be interesting not to only focus on co-patenting as an OI tool. Concerning the methodology, intensive experimentation with relevant parameter ranges is needed to attain significant and robust findings. The heavy computational requirement of ABM is still a challenge despite the computing power is increasing. In addition, experiments result in outcome distributions rather than point predictions. The outputs are mainly useful for qualitative insights rather than quantitative reasoning.

Data availability

Data will be made available on request.

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