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A system dynamics approach to modelling eco-innovation drivers in companies: Understanding complex interactions using machine learning

Carlos F. A. Arranz

Greenwich Business School, University of Greenwich, London, UK

Correspondence
Carlos F. A. Arranz, Greenwich Business School, University of Greenwich, Park Row, London, SE10 9LS, UK.
Email: c.fernandezdearroyabearranz@greenwich.ac.uk

Abstract

This paper examines the effect of drivers in the development of eco-innovation from a system dynamics perspective. While previous literature has made important contributions in identifying factors that influence the development of eco-innovations, there remains limited understanding of how these drivers act and interact in promoting its development. Therefore, there is a need to develop a framework of relationships and drivers that encourage and support eco-innovation in companies. This paper develops an integrated framework encompassing key internal, market and governmental factors and their complex interactions using principles of system dynamics and machine learning to address this gap. The research questions how these drivers interact in a dynamic and non-linear manner to influence the development of eco-innovation in companies and how can these interactions be effectively modelled and understood, considering the complexities of sustainable business practices and the limitations of traditional linear approaches. We empirically test these questions by using the Spanish Technological Innovation Panel database. The findings demonstrate that eco-innovation is not solely driven by isolated factors; instead, it emerges from the complex interplay between internal capabilities, governmental policies and market dynamics. By emphasising the synergistic effects of these drivers, the research offers a nuanced understanding of their systemic interactions. Furthermore, our analysis highlights the varying efficiency levels of different drivers, underscoring the pivotal role of environmental corporate policies and the strategic allocation of financial resources. In contrast, cooperation, market forces and regulations exhibit lower efficiency in driving eco-innovation processes. These insights not only advance theoretical knowledge but also provide valuable guidance for businesses and policymakers, offering a more holistic approach to fostering sustainable innovation.

List of abbreviations: AENOR, Asociación Española de Normalización y Certificación (Spanish Standardization Association; AFNOR, Association Française de Normalisation (French Standardization Association); ANN, artificial neural networks; CIS, Community Innovation Survey; CLD, causal loop diagram; CMB, common method bias; CMV, common method variance; ECM, environmental corporate management; INE, Instituto Nacional de Estadística (National Statistics Institute); MLP, multilayer perceptron; NRBV, natural resource-based view; PITEC, Panel de Innovación Tecnológica (Spanish Technological Innovation Panel); R&D, research and development; ROC, receiver operating characteristics; SEM, structural equation modelling; VIF, variance inflation factor.

KEYWORDS
complex process, drivers, eco-innovation, machine learning, system dynamics

1 | INTRODUCTION

In the context of pursuing a sustainable economy, eco-innovation has emerged as a common and necessary strategy for firm innovation (see, e.g., Arranz et al., 2020; Baldassarre et al., 2019; Dangelico et al., 2017). In fact, eco-innovation is identified as the most important contributor towards sustainable development by the European Parliament in the Lisbon Strategy targets for economic growth and competitiveness (Rodriguez et al., 2010). As a result of the increased demand for environmentally friendly products and services, as well as the growing societal relevance of sustainable development, firms have directed towards sustainable developments respectful with the environment. Grin et al. (2010) conclude that 'industrial transformation' involves adjustments in the production process, as well as in the required patterns when pursuing the route of sustainable development.

Since the recognition of the relevance of eco-innovation in achieving a sustainable environment and growth (see, e.g., García-Granero et al., 2020), a primary concern has been the need to develop a dynamic system for eco-innovation development, creating a framework of relationships and factors that encourage and support eco-innovation in companies (Kesidou & Demirel, 2012; Kiefer et al., 2019; Scarpellini et al., 2020). Thus, from an institutional point of view, administrations have understood this need and implemented actions, mainly regulation and financial support (Qi et al., 2021). Moreover, research has not been immune to it. Consequently, the literature, from natural resourced-based view (NRBV) and stakeholder theories, has considered not only the importance of factors internal to companies in the development of eco-innovation (Hart, 1995) but also the need for firms to establish relationships with stakeholders, as critical factors in the development of eco-innovation (Andersén, 2021; Jové-Llopis & Segarra-Blasco, 2018). This has made it possible to identify companies' internal and external factors as incentives and facilitators of eco-innovation. Notably, the literature has acknowledged three different categories of drivers for eco-innovation in companies: market forces, internal forces, and regulatory and policy forces (Arranz et al., 2021; Kiefer et al., 2019).

However, while the literature has made important contributions in identifying factors that influence the development of eco-innovation, there are limitations in understanding how these factors act in promoting its development. The main limitation arises from the fact that previous research has analysed the relationship between drivers and eco-innovation without considering that this process is dynamic and complex,[1] including the interaction between drivers in the development of eco-innovation. This has meant that results on the eco-innovation process have not been conclusive in determining factors and explaining how they interact (see, e.g., Cheng & Shiu, 2012; Horbach, 2016 and Jové-Llopis & Segarra-Blasco, 2018).

First, most papers have approached the study of eco-innovation development from an external perspective, considering how input variables (drivers) directly affect eco-innovation, forgetting about the effect that interactions between drivers can have in producing eco-innovations. The importance of the interactions has been highlighted, especially in recent research in innovative development, which has pointed out the significance of investigating the interactions between processes, as generators of synergistic and complementary effects (Ballot et al., 2015; Doran, 2012), being able to produce surprising effects on output variables. Therefore, investigating how drivers interact in the eco-innovation development process, facilitating it or generating synergistic processes, is an important issue to be studied.

Second, previous studies have analysed the relationship between drivers and eco-innovation without considering that this process is dynamic and complex (García-Granero et al., 2020; Jové-Llopis & Segarra-Blasco, 2020). This means that to the classic limitations of the diversity of surveys and the variety of measures used, which make generalisation difficult (García-Granero et al., 2020; Horbach, 2016), we can add the limitation that econometric models have in modelling complex relationships, as it is shown that most analyses do not exceed 40% explained variance, generating difficulties in modelling dynamic systems for eco-innovation.[2] That is, there is abundant and important research on the identification of factors that affect the development of eco-innovation, concluding whether they are significant or not (see, e.g., Jové-Llopis & Segarra-Blasco, 2018, 2020); however, studies that deal with how various drivers affect eco-innovation are limited and with inconclusive results. For example, the question of quantifying and prioritising how drivers affect eco-innovative development has not been resolved, which is an important issue from the perspective of business decisions and the development of environmental policies (D'Amato et al., 2021; Elmagrhi et al., 2019), considering the limited resources and the need to identify what the critical factors are in the development of eco-innovation. Moreover, while there is consensus on the positive effect of internal factors to the company (such as innovation capability or green corporative management) and institutional factors (such as regulations and financial support), this cannot be extrapolated to market factors. In fact, the literature shows contradictory results in terms of how the market affects eco-innovation. While a group of studies consider that the market has a positive

[1]Following Sterman (2000), a complex process is characterised, among other things, by constant changes, non-linearity and self-organisation. From a structural point of view, there are two characteristics of complex processes: the multiplicity of interactions and the diversity of agents that intervene in it (Arranz & Fernandez de Arroyabe, 2010).

[2]Some studies use structural equations model (SEM) in modelling the impact of the drivers in the eco-innovation. SEM combines the creation of a latent variable, with factor analysis, with a linear regression model. This generates a greater loss of variance in the explanation of the model, as a consequence of combining the two statistical models. For further details, refer to Holland et al. (2017) and Sardeshmukh and Vandenberg (2017).

impact (see, e.g., Rennings et al., 2006, Veugelers, 2012), other researchers have not observed any statistically significant relationships (Kesidou & Demirel, 2012; Kiefer et al., 2019). Unlike previous literature that has argued that the lack of consensus is based on discrepancies of measures in different geographical and sectoral areas, we argue that it derives from the low explained variance of market factors with respect to institutional and/or internal factors of the company, which, added to the low explanatory power of the model, justifies the variability of the results of these factors.

Therefore, the study of eco-innovation will require the solving of previous limitations and approaching the research from a more realistic, non-linear and complex perspective, which will allow adequate modelling of these systems to find out how the various drivers interact. In this context, our paper addresses this gap. First, from a methodological point of view and using a systems approach (Bergek, 2019; Bergek et al., 2008),[3] we assume, as in previous literature, that there are three categories of eco-innovation drivers: internal, market and governmental, considering these as input variables; and as an output variable, the eco-innovation developed by companies. Moreover, in line with Wu and Marceau (2002), we consider that drivers interact in non-linear and dynamic processes towards the development of eco-innovation. To do this, following Sterman (2000), we use the theory of dynamic systems, which combined with simulation methods will allow us to deduce the interaction between the drivers. Thus, we will be able to solve previous limitations of the literature, which have exclusively considered the direct impact of drivers in eco-innovation (Arranz et al., 2021). Second, from an instrumental point of view, we will combine both regression analysis and artificial neural networks (ANNs) in our modelling. Thus, to the explanatory power of the regression models, we can add the capacity of ANNs in the analysis of complex problems,[4] determining all interactions through learning algorithms. This will allow us to solve previous limitations of regression models, providing a higher level of explanatory variance, which will result in a better understanding and quantification of how various drivers influence eco-innovation development (Arranz et al., 2022). Last, we use the Spanish Technological Innovation Panel (PITEC) as our database, which is the Spanish counterpart of the EU Community Innovation Survey. The usage of this widely utilised database will enable us to compare and generalise the results. The final sample comprises of 5,221 companies in the manufacturing sector.

The main contribution of this paper lies in its innovative approach to understanding and modelling the complex dynamics of eco-innovation grounded theoretically in the Natural Resource-Based View and Stakeholder Theory. By integrating a dynamic systems perspective and employing advanced machine learning techniques, the study goes beyond the limitations of traditional linear analyses. It delves into the intricate interplay and feedback loops among internal, market and governmental drivers, shedding light on how these factors synergistically influence the development of eco-innovation. This novel methodology not only provides a nuanced understanding of the multifaceted relationships between drivers but also offers a robust quantitative framework for comprehending their non-linear interactions. Furthermore, the use of the PITEC as a comprehensive dataset ensures the applicability and generalisability of the findings. Overall, the paper's significant contribution lies in advancing the field's understanding of eco-innovation processes, enabling more effective decision-making for businesses and policymakers striving towards sustainable economic practices.

Therefore, the contribution is framed in the field of environmental management, developing an approach to the modelling of eco-innovation from a dynamic point of view. Moreover, unlike previous studies, our contribution focuses, first, on the interconnection and interdependence of drivers; second, on the dynamic feedback processes between these drivers; and, third, on the resulting behaviours, studying the systemic interaction of variables that affect eco-innovation. In fact, our findings demonstrate that eco-innovation is not solely driven by isolated factors; instead, it emerges from the complex interplay between internal capabilities, governmental policies and market dynamics. By emphasising the synergistic effects of these drivers, our research offers a nuanced understanding of their systemic interactions. Furthermore, our analysis highlights the varying efficiency levels of different drivers, underscoring the pivotal role of environmental corporate policies and the strategic allocation of financial resources. In contrast, cooperation, market forces and regulations exhibit lower efficiency in driving eco-innovation processes. These insights not only advance theoretical knowledge but also provide valuable guidance for businesses and policymakers, offering a more holistic approach to fostering sustainable innovation.

2 | CONCEPTUAL FRAMEWORK

2.1 | Eco-innovation conceptualisation

The Eco-Innovation Observatory (2018, p. 8) defines eco-innovation as the 'introduction of any new or significantly improved product (good or service), process, organisational change or marketing solution that reduces the use of natural resources (including materials, energy, water and land) and decreases the release of harmful substances across the whole life-cycle'. In fact, this definition, in line with the Community Innovation Survey, describes eco-innovation as a type of innovation (product, process, organisation and marketing) with the goal of reducing pollution and keeping a sustainable economy. Horbach et al. (2012, p. 119) corroborate this conceptualisation of eco-innovation as an innovation, defining it as 'product, process, marketing, and organizational innovations, leading to a noticeable reduction in environmental burdens'. Bossle et al. (2016), for their part, specify that the objectives of eco-innovation are to minimise the environmental effect of business operations, adhere to environmental regulatory standards, and increase energy savings.

Therefore, considering eco-innovation with environmental innovation, it is to be expected that there will be a parallel in the

[3]In Bergek (2019) and Bergek et al. (2008), it can find this perspective, considering the innovation as systems.

[4]See Somers and Casal (2009) and Minbashian et al. (2010) for more detail on the comparison between ANNs and regression models in complex problems.

innovation and eco-innovation development process (Arranz et al., 2020). As widely established in the literature, the development of innovation is characterised by the uncertainty and risks of developing this process (Jalonen, 2012; Jové-Llopis & Segarra-Blasco, 2020; López Pérez et al., 2023; Teece et al., 2016). This is, on the one hand, the technical uncertainty, to assess both the results and the time they were obtained, and, on the other hand, the uncertainty of the market, as a consequence of the need for consumer acceptance of eco-innovations. Moreover, similar to the innovation literature, it is to be expected that certain internal and external factors of companies (drivers) can facilitate this process, reducing risk and mitigating uncertainty.

While there is a similarity between the conceptualisation of eco-innovation and other types of innovation, there are also some differences. The first difference is that, while traditional types of innovation target economic profits, eco-innovation targets both economic and environmental benefits (Acebo et al., 2021; Janahi et al., 2023; Oh et al., 2020; Zhang & Walton, 2017). The second difference between innovation and eco-innovation is shown in the phenomenon called the 'double externality' (Arranz et al., 2020; Dangelico, 2016). That is, while the development of eco-innovation supposes an internal cost for companies, the public character of eco-innovation and its social benefit means that other companies can assume and imitate it without incurring costs. Therefore, the company is not incentivised to invest in eco-innovation. The last difference is the role that regulations and incentives play in eco-innovation as compared with traditional innovations. Previous research highlights the positive effect of environmental regulations and policies on eco-innovations (Costantini et al., 2017; Doran & Ryan, 2016).

2.2 | Drivers of eco-innovation: theoretical framework

As a theoretical framework, we employ the NRBV[5] and stakeholder theory,[6] which complement each other to explain firms' decisions to eco-innovate. The theories emphasise the role of external drivers of eco-innovation (Hart, 1995; Sarkis et al., 2010), noting that proactive firms manage their interaction with the natural environment through the integration of stakeholders. In fact, the NRBV highlights the engagement of stakeholders as a key driver of pollution reduction (Andersén, 2021; Katsikeas et al., 2016; Roxas et al., 2017; Zhang & Walton, 2017). Moreover, stakeholder theory has noted that stakeholder pressure exercised by customers, regulators, suppliers and competitors is a driver of eco-innovation (Horbach, 2008; Rennings & Rammer, 2011). Researchers in the area of eco-innovation have categorised external eco-innovation drivers into two groups: regulatory and policy forces and market forces (Horbach, 2008; Horbach et al., 2012; Kiefer et al., 2019).

Regarding the external regulatory and policy forces as drivers for eco-innovation, the literature centres on the effect that government regulatory forces and subsidies, or financial support, have had on the development of eco-innovations (Bimonte et al., 2023; Fischer & Pascucci, 2017). Regulations and subsidies push firms to invest in environmental innovation (Horbach et al., 2012; Kesidou & Demirel, 2012; Kiefer et al., 2019; Veugelers, 2012). For example, Directive 2009/125/EC determines the framework for the eco-design requirements for ecological products (Bovea & Pérez-Belis, 2012); XP X30-901 (AFNOR) and BS 8001 (British Standard) are certifications to promote zero waste and product recycling. Kiefer et al. (2019) and Kesidou and Demirel (2012) point out that governments offering incentives, tax breaks or feed-in tariffs for companies adopting renewable energy sources create a favourable environment for eco-innovation in the energy sector. Therefore, in line with previous research, it can be affirmed that the existence of a regulatory framework and public financial support should enable the eco-innovation process, having a significant impact on companies' decisions to develop them.

Market forces have traditionally been acknowledged as important external factors driving innovation decisions (Prajogo & Ahmed, 2006). Previous studies note that eco-innovation has recognised the environmental consciousness of consumers as a driver of eco-innovation demand (Hojnik & Ruzzier, 2016; Jansson, 2011). The proactive attitude of consumers towards ecological products has been considered as a driver for sustainable product development (Demirel & Kesidou, 2019). For example, the growing consciousness of environmental concerns and a preference for sustainable transportation have resulted in an increased demand for electric vehicles (Larson et al., 2014). Consequently, automotive manufacturers are addressing this demand through innovations in the electric vehicle sector, encompassing the development of extended-range batteries, improvements in charging infrastructure and the exploration of eco-friendly manufacturing practices. Therefore, companies find a new market as a business opportunity, fostered by the consumer's attitude towards the consumption of green products.

Moreover, in a similar way to innovation, NRBV has emphasised the importance of factors internal to the company as drivers of eco-innovation. Thus, the possession of resources and capacities has been highlighted as a key factor in the development of eco-innovation (Horbach, 2016; Jové-Llopis & Segarra-Blasco, 2018, 2020; Kiefer et al., 2019). In addition to this static approach to identifying resources and capabilities of a firm, we emphasise internal processes and organisational dynamics developed with these resources, in line with the purpose of this research, focused on the dynamics of processes. That is, grounded in the theory of dynamic capabilities (Barney, 2001; Zahra et al., 2006), and following Eisenhardt and Martin (2000), who have characterised dynamic capabilities as an

[5]The Natural Resource-Based View (NRBV) is a theoretical framework in strategic management and organisational theory that focuses on the role of natural resources in a firm's competitive advantage and performance (Hart, 1995). It is an extension of the Resource-Based View (RBV) of the firm, which asserts that firm-specific resources and capabilities are the primary sources of competitive advantage. NRBV specifically emphasises the unique characteristics of natural resources, such as their scarcity, immobility and imperfect imitability, as sources of sustainable competitive advantage.

[6]Stakeholder theory is a concept in business ethics and management that suggests that businesses and organisations should consider the interests of various stakeholders, beyond just shareholders, in their decision-making processes. Stakeholders are individuals or groups who have an interest in the activities of a business and can affect or be affected by the organisation's actions, policies and objectives (Horbach, 2008).

identifiable process, we assume that the firm must have the ability to develop eco-innovation, deploying resources and capabilities, and using organisational processes to achieve these objectives. Moreover, following Teece (2007), who states that firms' capabilities enable the development of innovation processes, we consider the ability to develop certain processes as internal to the organisation, conceptualising them as drivers of eco-innovation.

In this research, three internal drivers of eco-innovation are considered: innovation capability, environmental corporate management (ECM) and cooperation agreements (see Table 1). Innovation capabilities are defined as the capacity of companies to manage resources, using organisational processes to reach some innovation goals (Teece, 2007; Teece et al., 2016). Li et al. (2020) and Arranz et al. (2020) have found a parallel in the development of innovation and eco-innovation, pointing out the similarity of the processes, which makes the competencies and skills in innovation acquired by companies a driver of eco-innovation. Indeed, possessing a strong innovation capability has acted as a catalyst for the development of eco-innovation. For instance, Kumi (2023) emphasises the case of Tesla, where innovations like the Powerwall and Powerpack exemplify their prowess in energy storage solutions. These products facilitate the efficient storage of renewable energy for subsequent use. Tesla's success in developing effective energy storage solutions directly tackles a challenge associated with renewable energy sources, namely, intermittency. This not only addresses a crucial issue but also adds to the wider eco-innovation landscape by facilitating the seamless integration of renewable energy into the grid.

The second internal driver is ECM. Banerjee (2002, p. 181) puts forward the notion of 'corporate environmentalism', which he describes 'as the organization-wide recognition of the legitimacy and importance of the environment in the formulation of organization strategy, and the integration of environmental issues into the strategic planning process of a firm's environmental orientation and its business strategy'. In this context, the literature highlights the importance of developing corporate capacities compatible with the environment, which is deemed as a key driver for improving eco-innovation strategy (García-Granero et al., 2020; Li et al., 2020). For example, Tesla, the electric vehicle and clean energy company, is recognised for its robust commitment to environmental sustainability (Kumi, 2023). In particular, the literature considers as a good indicator of a company's environmental friendliness, the amount environmental objectives included in production and operations plans (Buil-Carrasco et al., 2008; Orazalin, 2020).

The last internal driver of eco-innovation is the ability to establish collaborative agreements with other firms or organisations (Acebo et al., 2021; Horbach, 2016). As established in the innovation literature, the establishment of cooperation agreements permits sharing risks related to innovative activities, generating a stock of shared knowledge and positively influencing the companies' decisions towards the development of eco-innovation (Arranz et al., 2020). As an example, prominent fashion enterprises such as Adidas, H&M and Kering united in 2019 to form The Fashion Pact, a coalition dedicated to tackling environmental issues within the industry (Pérez-Bou & Cantista, 2023). Centred on climate, biodiversity and oceans, the pact facilitates collaboration among participating companies, fostering the exchange of knowledge, resources and best practices to propel eco-innovation. This collaborative effort encompasses the development of sustainable materials, the adoption of circular fashion practices and the mitigation of environmental impact in supply chains.

TABLE 1 Drivers of eco-innovation

Drivers	Variables	References
Internal	• Innovation capabilities • Environmental corporate management (ECM) • Cooperation agreements	Acebo et al. (2021); Arranz et al. (2020); Banerjee (2002); del Río et al. (2016); Demirel and Kesidou (2019); Fischer and Pascucci (2017); García-Granero et al. (2020); Hojnik and Ruzzier (2016); Horbach et al. (2008, 2012, 2016); Jansson (2011); Kesidou and Demirel (2012); Li et al. (2020); Prajogo and Ahmed (2006); Triebswetter and Wackerbauer (2008); Veugelers (2012)
Governmental	• Regulation • Public financial support	
Market	• New for the market	

3 | RESEARCH MODEL AND HYPOTHESES

Existing studies examining the connection between drivers and eco-innovation have overlooked the dynamic and intricate nature of this process, as noted by recent research (see, e.g., Arranz et al., 2021; Gracia-Granero et al., 2020; Russell & Smorodinskaya, 2018; Jové-Llopis & Segarra-Blasco, 2020). While there is ample research on identifying factors impacting eco-innovation and determining their significance (e.g., Jové-Llopis & Segarra-Blasco, 2020, 2019), studies exploring how diverse drivers affect eco-innovation are scarce and yield inconclusive results. The critical issue of quantifying and prioritising the impact of drivers on eco-innovation remains unresolved, posing challenges for business decisions and environmental policy development, given resource limitations and the necessity to pinpoint critical factors in eco-innovation development (D'Amato et al., 2021; Elmagrhi et al., 2019). Therefore, our research question addresses how internal, market and governmental drivers interact dynamically and non-linearly to influence eco-innovation development in companies. Additionally, we aim to effectively model and comprehend these interactions, considering the complexities of sustainable business practices and acknowledging the limitations of traditional linear approaches.

3.1 | System dynamics theory

As indicated in the introduction, for our modelling, we are going to use a system dynamics perspective. Since Forrester's early work in system engineering, this approach has been utilised in a wide variety of areas, such as the modelling of complex ecological and economic systems (Walters et al., 2016; Zhao et al., 2018) and addressing the social implications of the behaviour of the system (Wu & Marceau, 2002). Sterman (2000) points out that the system dynamics approach describes and simulates dynamically complex problems by the identification of interactions between variables and processes, which drive the behaviour of the system.

A system dynamics perspective proves invaluable in interpreting the catalysts behind eco-innovation due to its holistic and dynamic approach to deciphering intricate relationships and feedback loops within a system. Eco-innovation encompasses a multitude of interconnected factors, ranging from technological advancements and regulatory frameworks to market dynamics and consumer behaviour. Through a systems dynamics perspective, we can model these intricate interconnections, gaining insight into how alterations in one facet of the system can ripple through others. Additionally, system dynamics places a spotlight on feedback loops, crucial for comprehending how modifications in one segment of the system can impact the entire system. In the context of eco-innovation, these feedback loops may encompass the influence of consumer awareness on market demand, subsequently shaping corporate strategies and technological progress. A profound understanding of these feedback loops proves indispensable in formulating effective strategies for eco-innovation.

The system dynamics theory considers that complex systems are comprised of elements, parts or subsystems, stressing the interaction between elements and the system evolution (Bergek, 2019; Bergek et al., 2008; Russell & Smorodinskaya, 2018; Sterman, 2001; Walters et al., 2016; Zhao et al., 2018). That is, the interaction between components is the fundamental element of modelling dynamic systems. Interactions are defined as processes by which two or more variables affect each other, implying the idea of a bidirectional effect, as opposed to a unidirectional causal effect (Sterman, 2001, 2000). Therefore, the input variables interact in a dynamic process, where the interactions between components produce an effect on their initial value. Sterman (2000) models the dynamic interaction between components, conceptualising it as a feedback loop, in which the effect of a variation in any component propagates through the loop and returns to the component, affecting the initial value. These loops can be distinguished between a reinforcing loop, in which a reinforcement of the initial value occurs, or a balancing loop, in which a weakening arises (see Figure 1). Two consequences can be derived from the effect of the dynamic interaction between components: first, a strengthening/weakening in the components as a consequence of the interaction and, second, the output variables of the system are left strengthened/weakened as a consequence of the interaction of the input variables, with respect to the non-existence of interaction.

This last point is being especially considered in innovation research, addressing the reinforcement or synergistic effect of the interaction between technological and non-technological innovation and its effect on firm performance (see Arranz et al., 2019; Ballot et al., 2015; Doran, 2012). From the perspective of complementarity, emphasis has been placed on the importance of the interaction

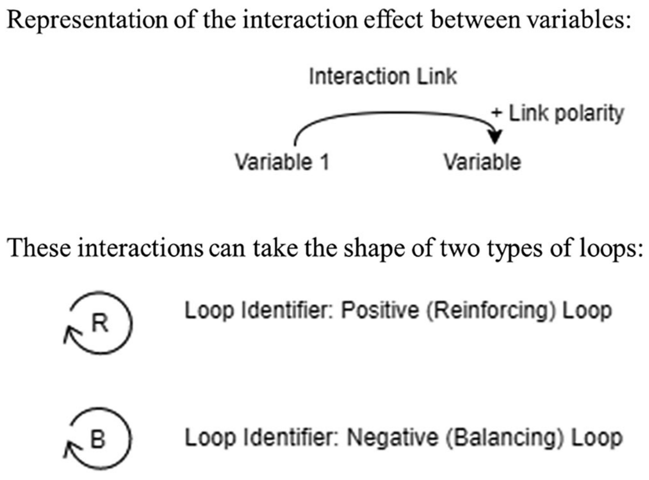


FIGURE 1 Link polarity and feedback loops

between variables (Milgrom & Roberts, 1995), indicating that engaging in more than one activity boots the returns of engaging in more of another. Camisón and Villar-López (2014) and Arranz et al. (2019) justified this synergic or complementary effect by stating that it derives from shared resources, competencies and routines, through the generation of economies of scale and learning processes in the development of innovation processes. Therefore, the consequence of synergistic effects between dynamic processes is especially important in social and business systems, since the interactions between these processes can lead to surprising phenomena.

System dynamics modelling typically adopts two forms: (i) qualitative or polarity analysis, representing dynamic factor interaction, using causal loop diagrams (CLDs) (Richardson, 2011; Sterman, 2000; Walters et al., 2016), and (ii) quantitative modelling, which simulates the dynamic effects of factors and their interaction. More in detail, Sterman (2000) introduces polarity analysis as interaction diagrams (CLDs), representing the dynamic interaction between factors. CLDs consist of arrows (causal influences) between different factors and pair-wise factor polarities represented as positive (+), this is, when two factors are in interaction, the increase of one factor causes an increase in another, or negative (−), which is the contrary of a positive influence. CLD diagrams enable the identification of circular causality between factors (feedback loops) (Richardson, 2011). Figure 1 and Table 2 show the CLD elements.

3.2 | Polarity analysis: The dynamics of interaction in eco-innovation

In our modelling, we propose that the development of eco-innovation is fostered by a series of factors (drivers), which promote/facilitate the development of eco-innovation. We take a systems approach in the development of eco-innovation, where the input variables are the drivers and the output variable is the eco-innovation. Thus, the development of eco-innovation will involve the development of a dynamic process, where the input variables (drivers) interact

TABLE 2 Link polarity definitions

Symbol	Interpretation	Equation
	If X increases (decreases) then Y increases (decreases)	$\frac{\partial y}{\partial x} > 0$
	If X increases (decreases) then Y decreases (increases)	$\frac{\partial y}{\partial x} < 0$

with each other to achieve the output variable. We consider four levels of interaction. Figure 2 shows the CLD of the dynamic of eco-innovation development in companies.

3.2.1 | First level: Interaction between internal drivers

From the internal point of view of the company, we consider three drivers of the firm in the eco-innovation development process: innovation capabilities, ECM and cooperation agreement. Following our theoretical approach, it is to be expected that these internal drivers will interact with each other in a reinforcing loop. Moreover, this cycle of positive reinforcement among internal drivers is expected to have an incremental impact on the probability of developing eco-innovation.

In the first place, innovation capability and ECM are expected to interact with each other in a dynamic process of reinforcing both drivers in the eco-innovation development process. On the one hand, ECM is expected to incentivise the company's process innovations. That is, ECM, in the development of eco-innovation, needs not only the development of corporate capacities compatible with the environment, such as recycling, material usage reduction, pollution prevention and green design (Kesidou & Demirel, 2012) but also the compliance of eco-innovation objectives, which involve the development of resources and capacities for innovation (Arranz et al., 2019). Therefore, a firm will promote both eco-innovation and innovation capabilities. Thus, the innovation capabilities possessed by a company will be reinforced by the implementation of the ECM processes. On the other hand, innovation capabilities are expected to interact by reinforcing ECM. Innovation capabilities in the development of eco-innovation require the development of green capacities, which will be a positive reinforcement of the ECM, implementing environmental issues into the company's business strategy and environmental orientation.

Second, innovation capabilities in their eco-innovation development process interact reciprocally and positively with the development of cooperation agreements. On the one hand, the innovation process necessitates the possession of capacities and resources, which will reinforce cooperation agreement capabilities. Previous research has suggested that the benefits derived from cooperation not only comprise cost saving, risk sharing and access to financial resources or complementary assets but also improved ability to learn, knowledge allocation in the innovation process and quicker development of innovation (Eisenhardt & Schoonhoven, 1996; Hagedoorn, 1993). Therefore, innovation capabilities in the development of eco-innovation will reinforce the processes and capacities for establishing cooperation agreements, since, in Eisenhardt's terminology, cooperation agreements are processes in which resources and capabilities can be shared with other areas for the development of innovation and eco-innovation. On the other hand, an interaction of reinforcement of cooperation agreements towards the innovation capacities of an organisation is to be expected. Hence, the development of cooperation agreements in the establishment of eco-innovation entails a series of needs in its development. Arranz and Fernandez de Arroyabe (2012) point out that in the process of establishing cooperation agreements, the initial tasks are to identify the technological needs of companies, define the partner profile and search for partners. Thus, Agarwal and Selen (2009) and Beers and Zand (2014) show that the development of innovation processes allows companies to acquire skills in prospective innovation, which results in a capacity for scrutiny and identification of future collaboration agreements. These prospective competencies will allow the identification of both the innovation needs of the company and the identification of possible partners for the development of a cooperation agreement.

Finally, the interaction between ECM and cooperation agreements for innovation should provide mutual reinforcement. First, cooperative agreements in their development of eco-innovation processes will reinforce ECM. That is, cooperation agreements are recognised as important elements in the identification of both eco-innovation objectives and access to green capabilities (Horbach, 2016; Melander, 2018; Niesten et al., 2017), which will be a reinforcement of the company's ECM. Second, ECM in a company reinforces the development of cooperation agreements in the development of eco-innovation, as a way to access green capabilities and development of eco-innovation objectives, assuming a positive reinforcement of the development capacities according to existing cooperation.

Moreover, it has been confirmed that innovation capabilities, ECM and cooperation agreements individually have a positive effect on the subsequent development of eco-innovation (Cai & Zhou, 2014; Doran & Ryan, 2016; Frigon et al., 2020). In our case, we postulate that the interaction of internal drivers reinforces them in a feedback loop, where the three drivers are mutually reinforcing, which will result in a greater probability of eco-innovation than if the drivers did not interact. Hence, we propose the following:

> **Hypothesis H1.** Internal drivers interact positively with each other, forming reinforcing interaction, which positively affects the development of subsequent eco-innovation more than if they do not interact.

> **Hypothesis H1a.** Innovation capabilities in interacting with ECM positively affect the development of subsequent eco-innovation more than if they do not interact.

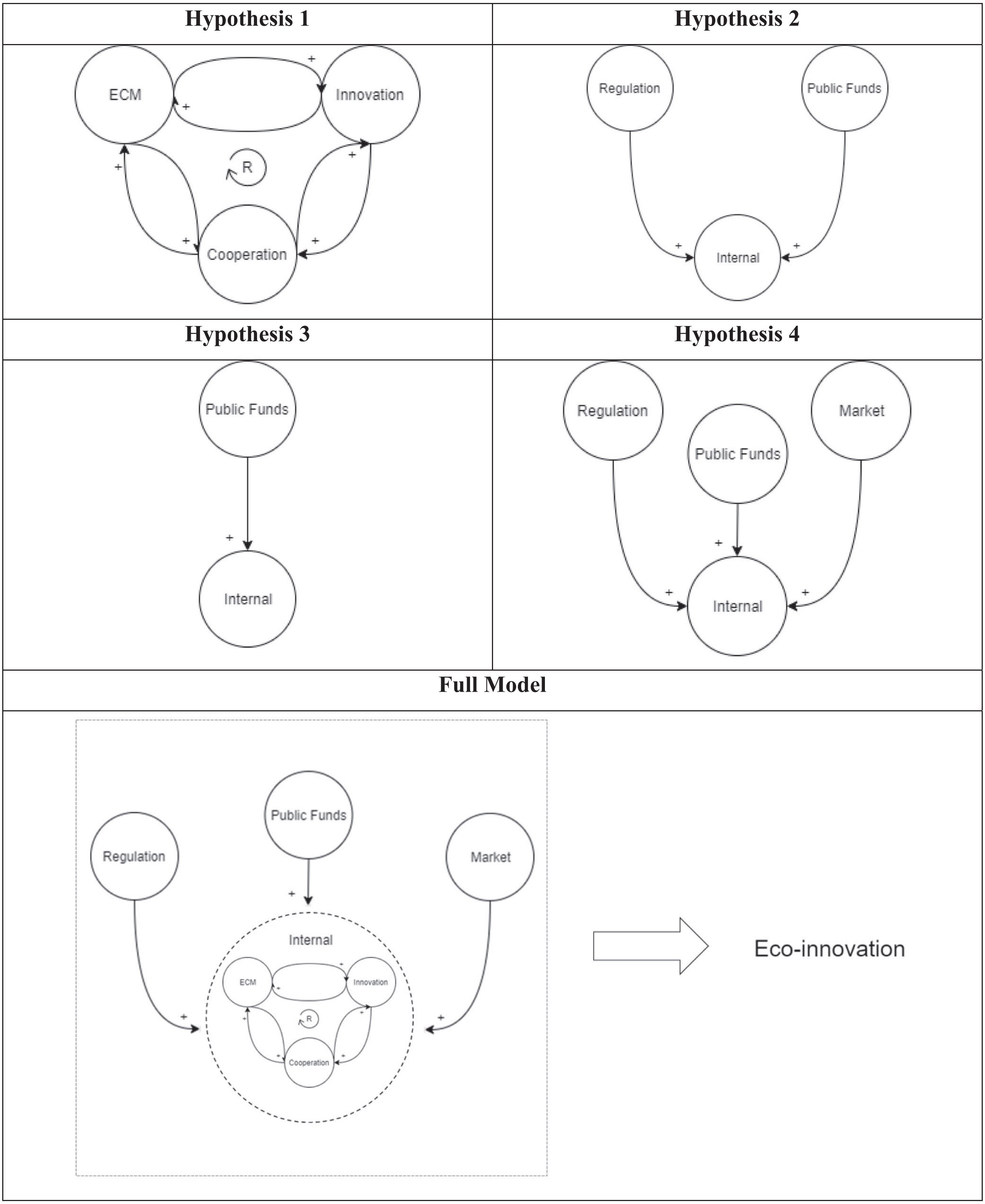


FIGURE 2 CLD of the dynamic of eco-innovation development in companies

Hypothesis H1b. Innovation capabilities in interaction with cooperation agreements positively affect the development of subsequent eco-innovation more than if they do not interact.

Hypothesis H1c. Cooperation in interaction with ECM positively affects the development of subsequent eco-innovation more than if they do not interact.

3.2.2 | Second level: Interrelation between governmental and internal drivers

In our model, we propose as external drivers the existing environmental regulation and the existence of financial support. Unlike the interaction between internal drivers that we consider bidirectional, in this case, we postulate a unidirectional interrelation, where the external drivers reinforce the internal drivers.

First, we consider that government regulation positively and significantly affects internal drivers. For example, the implementation of Directive 2009/125/EC for the creation of eco-design criteria for energy-related goods (Bovea & Pérez-Belis, 2012) or the adoption of environmental quality-control systems such as ISO 9001 or/and 14001, as compulsory regulations, is an incentive for the development of corporate decisions on sustainability, reinforcing ECM in the company. Moreover, the existence of regulation can be seen as a facilitator of innovation capabilities in the firm. For example, the certification XP X30-901 (French Standardisation Association, AFNOR), which aims at the development of good practices to attain a circular economy model (AFNOR, 2018), or the Spanish Standardisation Association (AENOR), which launched a zero-waste certification in organisations through the product development process, and by facilitating assistance for the application of the circular economy models within companies (AFNOR, 2018). Additionally, Li and Yu (2011) point out that through standards and certifications, communication and organisation between partners are facilitated, paving the way for the establishment of cooperation agreements between companies.

Second, the existence of financial support is postulated as a reinforcement of the internal drivers. Siguaw et al. (2006) have emphasised innovation capabilities as an orientation towards the development of innovation. In this sense, the existence of external funding will encourage the organisation's orientations towards eco-innovation, by allowing funding to be allocated to obtaining resources and increasing skills and abilities in eco-innovation. In this same line, the company's ECM will also be reinforced by the existence of external funding, allowing the financing of new strategic lines of sustainability development (Fischer & Pascucci, 2017; Gallego-Alvarez et al., 2017; Stojčić, 2021). Moreover, Arranz and Fernandez de Arroyabe (2012) highlight cooperation agreements as a constant negotiation between partners. In this context, the establishment and management of cooperation agreements require the consumption of time and effort on the part of the organisation, which will be facilitated by the existence of financial resources. Hence, we propose the following:

Hypothesis H2. The existence of governmental drivers in interrelation with internal drivers will produce a reinforcing effect on the internal drivers, positively affecting the development of later eco-innovation more than if internal drivers acted individually.

Hypothesis H2a. The existence of regulation in interrelation with internal drivers will produce a reinforcing effect on the internal drivers, positively affecting the development of later eco-innovation more than if internal drivers act individually.

Hypothesis H2b. The existence of public funding in interrelation with internal drivers will produce a reinforcing effect on the internal drivers, positively affecting the development of subsequent eco-innovation more than if internal drivers acted individually.

3.2.3 | Third level: Interrelation between market drivers and internal drivers of eco-innovation

In line with previous hypotheses, we consider that the market drivers will reinforce internal drivers. The consumer's proactive attitude towards the consumption of environmentally friendly goods has been considered as a driver for the introduction of new green products (Arranz et al., 2021; Demirel & Kesidou, 2019) or as an incentive for new companies to work in these sectors (Annunziata et al., 2018). On the one hand, market drivers will positively affect an organisation's ECM. In fact, the role of ECM is to define eco-innovation targets, which will be facilitated by the market drivers, by understanding consumer and market needs. On the other hand, a barrier to the innovation process is the uncertainty of the market. The existence of market drivers allows the mitigating of the uncertainty and risks of launching a product to the market, encouraging innovation capabilities. Finally, Gans and Stern (2003) and Hagedoorn (2002) have pointed out that market drivers encourage the development of cooperation agreements, clarifying both the future objectives of the same, as well as possible partners. Hence, we propose the following:

Hypothesis H3. Market drivers in interrelation with internal drivers will produce a reinforcing effect of the internal drivers, positively affecting the development of later eco-innovation more than if internal drivers acted individually.

3.2.4 | Fourth level: Governmental and market drivers in interrelation with internal drivers

The last stage of our modelling raises the interrelation of governmental and market drivers with internal drivers in the development of eco-innovation. First, in line with previous hypotheses, it is to be expected that the joint interrelation of governmental and market drivers will also produce a reinforcement on internal drivers. Second, positive reinforcement is also to be expected in the development of eco-innovation, when both government and market drivers act jointly with the internal drivers. Hence, we propose the following:

> **Hypothesis H4.** Market and governmental drivers in interrelation with internal drivers will produce a reinforcing effect of the internal drivers, positively affecting the development of later eco-innovation more than if internal drivers acted individually.

4 | EMPIRICAL STUDY

4.1 | Sample

The data for this study were obtained from the Technological Innovation Panel (PITEC), which has been carried out by the National Statistics Institute (INE). The survey reproduces for Spain the standardised questionnaire utilised by the Community Innovation Survey (CIS) (Fagerberg et al., 2012), following the Oslo Manual and the Frascati Manual guidelines. CIS is a programme initiated by the European Commission and implemented in European Union member states. Its primary objective is to collect data on innovation activities in various sectors of the economy. As key aspects of the database, we can find that CIS collects data through surveys conducted among businesses. These surveys cover various aspects of innovation, including technological innovation, non-technological innovation, collaboration efforts and sources of information for innovation. Moreover, CIS surveys a wide range of sectors, from manufacturing and services to agriculture. It aims to provide a comprehensive view of innovation activities across different industries. The data collected through CIS have been used for policymaking, research and analysis. It helps policymakers understand the innovation landscape, identify trends and formulate strategies to promote innovation and competitiveness in the European economy.

The study's reference periods are 2010–2011 ($t-1$) and 2012–2013 (t). After a filtering procedure,[7] the final sample includes 5,233 firms in the manufacturing sector. PITEC contains rich firm-level data concerning a company's profile (e.g., sales, employment, geographical market and industrial sector) and its innovation activity (innovation expenditures and output, cooperation agreements, public support and obstacles for innovation).

Regarding the sample characteristics, we observe a diverse range of sizes, covering the entire spectrum from microenterprises (10.3%) to small businesses (40.6%), medium-sized enterprises (33.6%) and, finally, large enterprises accounting for 15.5%. Concerning the represented sectors, the sample encompasses a balanced representation of all industrial sectors. Finally, it is noteworthy that 41.3% of the companies belong to an industrial group, while the remaining companies (58.7%) operate independently.

4.2 | Measures

4.2.1 | Eco-innovation measure

Following the PITEC questionnaire, this measures eco-innovation of the organisation throughout the level of environmental innovative activity, in the period 2012–2013 (t), to accomplish two objectives: (i) the consumption of less energy per unit and (ii) the production of less environmental impact. Both objectives are measured on a scale of 1 to 4: where a value of 1 is given if the eco-innovation activities are high, 2 if they are intermediate, 3 if they are low and 4 if they are null. In line with Arranz et al. (2021) and Costantini et al. (2017), the dependent variable was formed as a cumulative index of the two previous types of eco-innovation (*eco-innovation*), its resulting range being between 2 and 8. This method has advantages over other methods such as factor analysis, in that we have no loss of variance, it maintains the typology of the measuring scale and it allows us to measure eco-innovation in all its breadth, both in diversity and intensity. Methodologically, there are two requirements: first, a high level of correlation between variables (correlation .794) and, second, that the scales of the variables are consistent with each other.

4.2.2 | Drivers' measures

All drivers' measures relate to the period 2010–2011 ($t-1$). For the purpose of this research, the drivers are categorised as internal drivers, market drivers and governmental drivers.

This study employs three variables to examine internal drivers: ECM, innovation capability and cooperation. First, ECM is measured, from a performance perspective (Banerjee, 2002), by the environmental objectives comprised in production plans and operations in period ($t-1$). The PITEC questionnaire incorporates three objectives: (i) producing less environmental impact; (ii) adherence with environmental, health or safety regulations; and (iii) consuming less energy per unit. The objectives are measured on a scale of 1 to 4: where a value of 1 is given if the eco-innovation activities are high, 2 if they are intermediate, 3 if they are low and 4 if they are null. The variable was formed as a cumulative index of the three previous items (Cronbach alpha: .895), following the previous measure's methodology. Second, following Li et al. (2020) and Arranz et al. (2020), which found a parallel in the competencies and skills in innovation acquired by companies and eco-innovation, PITEC measures a company's capacity for innovation development if it implements these four types of innovation in period ($t-1$): product, process, organisation and marketing. Following the previous methodology, the measure for innovation capability is a cumulative index, as a result of the sum of the four typologies of innovation. The last variable is cooperation. In line with

[7] The specific criteria used for this filtering procedure include the firm's industry classification, the elimination of incomplete responses and microenterprises.

De Marchi (2012) that highlights the importance of cooperation between companies as a driver of eco-innovation, PITEC measures whether a company has developed cooperation agreements with other firms for innovative development. In this case, PITEC uses the value of 4 if the company uses the agreements of cooperation with high frequency and 1, with low frequency for the development of innovation activities during period $t-1$.

Governmental drivers refer to actions taken by the government to embrace eco-innovation in firms. The first governmental driver is the regulation of environmental activities. For measuring the level of regulation, PITEC contains a variable that measures whether Spanish regulatory requirements have a high, medium, low or null orientation towards eco-innovation. This variable is rated on a scale of 1 to 4 and measures the perceived regulation by companies. The second driver refers to public financial support. PITEC includes three categorises of public funding to measure the source of the funding received by the companies: (i) from local or regional governments; (ii) from the national government or (iii) from the European Union. To measure the level of the impact of public funding given to a firm to develop eco-innovation, this study adds up the three levels of financial support. This results in a public funding variable that is measured on a scale of 0 to 3 (Cronbach Alpha: .734).

The last independent variable is market drivers; companies find a new market as a business opportunity, fostered by the consumer's attitude towards the consumption of green products, as indicated by Demirel and Kesidou (2019). Therefore, PITEC captures this by assessing whether the company develops new products for the market. This is measured as a variable with a value of 1 if it was new to the market, and 0 if not.

5 | ECONOMETRIC MODELS

In our modelling, the input variables (drivers) correspond to the period ($t-1$) and the output variable (eco-innovation) to the period (t). The analysis has been carried out in two stages. First, we analyse the effect of each driver on the development of eco-innovation, and second, we examine the effect of the interaction between the various drivers.

5.1 | Estimation of the effect of drivers in eco-innovation

For the development of this question, we propose a simulation of the effect of the drivers in eco-innovation with ANN. Previously, for this simulation, we carried out an initial check, using regression analysis, to determine the direct effect of the drivers on eco-innovation, without considering the interaction between variables.

We estimated four following models in the analysis:

Model 1:

$$\begin{aligned} Eco-innovation\,(t) = \text{constant} &+ ß_1(ECM\,(t-1)) \\ &+ ß_2(Innovation\ capability\,(t-1)) \\ &+ ß_3(Cooperation\,(t-1)) + \text{e} \end{aligned}$$

Model 2:

$$\begin{aligned} Eco-innovation\,(t) = \text{constant} &+ ß_1(Public\ financial\ support\,(t-1)) \\ &+ ß_2(Regulation\,(t-1)) + \text{e} \end{aligned}$$

Model 3:

$$Eco-innovation\,(t) = \text{constant} + ß_1(New\ market\,(t-1)) + \text{e}$$

Model 4:

$$\begin{aligned} Eco-innovation\,(t) = \text{constant} &+ ß_1(ECM\,(t-1)) \\ &+ ß_2(Innovation\ capability\,(t-1)) \\ &+ ß_3(Cooperation\,(t-1)) \\ &+ ß_4(Public\ financial\ support\,(t-1)) \\ &+ ß_5(Regulation\,(t-1)) + ß_6(New\ market\,(t-1)) \\ &+ \text{e} \end{aligned}$$

Moreover, we combine regression analysis with machine learning methods, more specifically ANN. That is, to the explanatory power of regression models in causal analyses, we add the exploratory power of ANN models, especially in the case of the existence of non-linear relationships between input variables and multiplicity of interactions (Alpaydin, 2021). Arranz et al. (2022) point out that ANN is a powerful tool when dealing with complex, high-dimensional data and tasks that involve pattern recognition and non-linear relationships. Their versatility and ability to handle diverse data types make them a valuable asset in many domains. Arranz et al. (2021) also indicate that the combination of both methods allows us not only to know which variables affect the dependent variable but also to know how they are influencing. Therefore, we have carried out this second analysis, to determine not only which drivers have an impact, but also how the drivers' variables impact eco-innovation.

The simulation using ANN architecture considers the interaction and interdependence between drivers. For this, we have used a multilayer perceptron (MLP) (Figure 3). Of all the ANN models, we have focused on MLP, because, in addition to allowing non-linear data relationships to be modelled, its universality and versatility have been demonstrated compared to other types of neural networks (Mehrotra, 1997), which means that it can learn and represent any mathematical function, which makes them suitable for a wide variety of modelling and prediction tasks, obtaining a high level of model robustness. This architecture corresponds to a supervised network, which means that it allows comparing the predicted results to known values of the dependent variables. An MLP's network architecture consists of an input layer, hidden layers and an output layer. The hidden and output

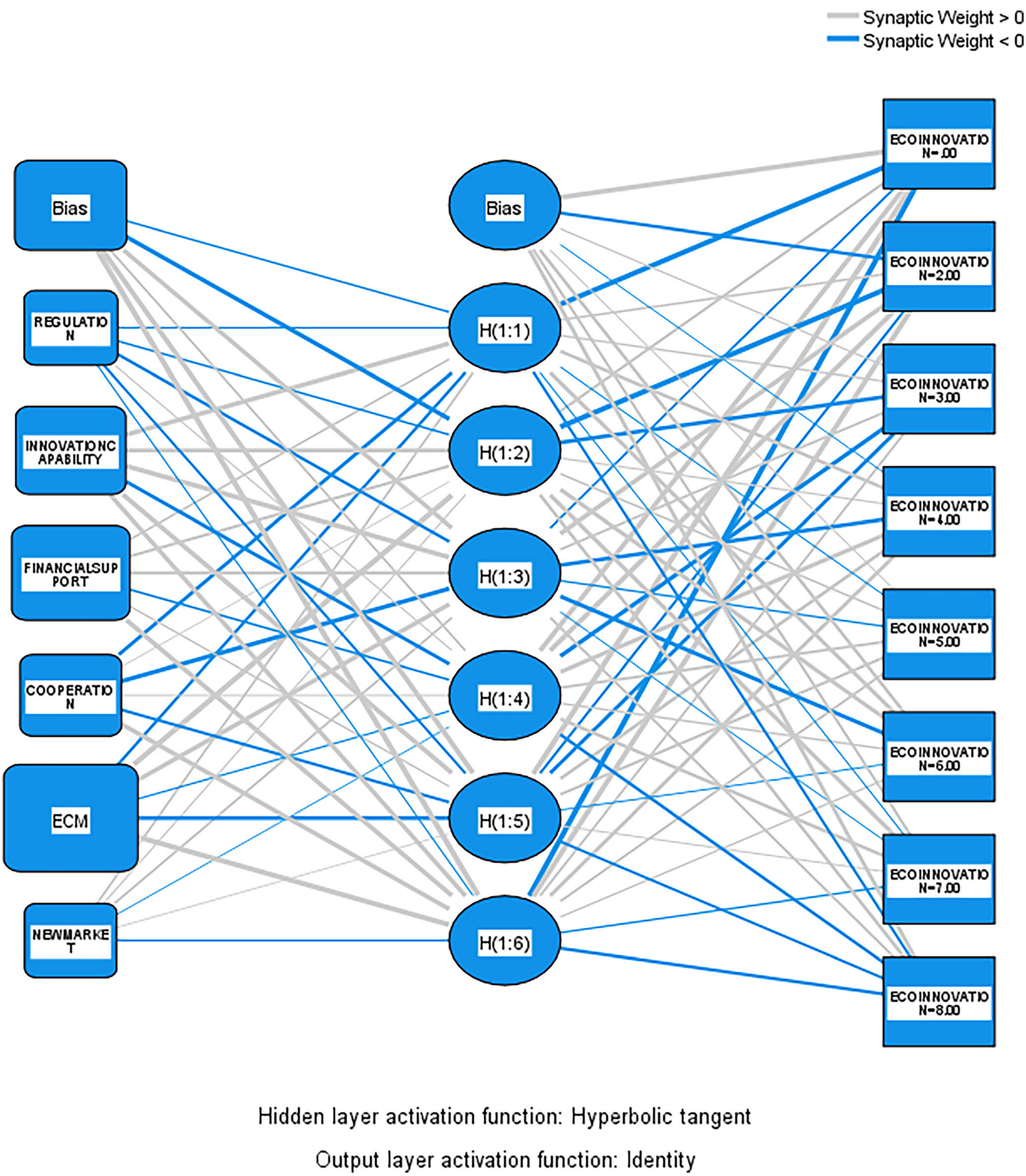


FIGURE 3 ANN-MLP architecture

layers' neurons, with their associated weights, are connected, which allows to analyse the interaction between input variables.

The design of the ANN-MLP architecture in this paper follows Wang (2007) and Arranz and Fernandez de Arroyabe (2010). Table 3 shows the procedure of design of the ANN-MLP architecture. In this procedure, we can distinguish two key points: (i) the choice of the number and size of the hidden layer and (ii) the choice of the learning algorithm. First, while the number of independent and dependent variables determines the number of inputs and outputs of the proposed network (respectively), the size and number of hidden layers are

TABLE 3 Steps of the ANN procedure

1. Choice of the ANN typology	2. Design of architecture of ANN-MLP	3. Choice of the learning algorithm	4. Learning stage	5. Sensitive analysis
We choose the ANN architecture with multilayer perceptron (MLP)	The network accuracy and the efficiency are dependent on various parameters: Hidden nodes, activation functions, training algorithm parameters and characteristics such as normalisation and generalisation. The number of inputs and outputs is given by the number of available input and output variables. The number and size of hidden layers is determined by testing several combinations of the number of hidden layers and the number of neurons. The types of activation functions, for the hidden layer, we used a sigmoid logistic (values from 0 to 1) and a hyperbolic tangent (−1 to 1), and a SoftMax function for the activation function of the output layer.	We use backpropagation. This learning algorithm determines the connection weights of each neuron, readjusting the weights and minimising the error.	To avoid problems of overfitting and consumption of processing time, we divided the sample randomly into three subsamples (training, testing and holdout). In the training stage, the weights and links between nodes are determined, with the aim of minimising the error. In the validation stage, the generalisability of the obtained architecture is checked. Lastly, the holdout data are used to validate the model.	A sensitive analysis is developed to quantify the influence of each input variable on the output variables.

established through testing various configurations of hidden layers and the number of neurons in the layer,[8] using a trial-and-error approach (Ciurana et al., 2008; Mehrotra, 1997). That is, the chosen architecture is evaluated with different activation functions, with the optimal architecture being one that minimises the error. Taking the input and output variables into consideration, we establish the following model.

Model:

$$\begin{aligned} Eco-innovation(t) = f(&Innovation\ Capability(t-1); ECM(t-1);\\ &Cooperation(t-1); Regulation(t-1);\\ &Public\ support(t-1); New\ Market(t-1)) \end{aligned}$$

Second, regarding the learning algorithm selection, in this paper, we use a backpropagation algorithm. This learning algorithm decides each neuron's connection weights, readjusting the weights as needed and minimising the error. The equation for modifying the algorithm weights is shown below:

$$\Delta wji(n+1) = \varepsilon.\mu pi.xpi + \beta\Delta wji(n) \qquad \begin{aligned} &\text{Being}, wji = \text{weight neuron } i \text{ and } j\\ &n = \text{number of interactions}\\ &\varepsilon = \text{learning rate}\\ &\mu pi = \text{neuron } j \text{ error for pattern } p\\ &xpi = \text{output of neuron } i \text{ for pattern } p\\ &\beta = \text{momentum}\end{aligned}$$

From the equation, we can see that there are three critical variables: the number of interactions, the learning rate and the moment. Regarding the number of interactions (n), we have used 10,000.[9] As for the value of the learning rate (β), it controls the size of the change of the weights in each iteration,[10] and the learning rate usually has a

[8]The selection of a suitable amount of hidden neurons is critical; if too few neurons are employed, there will be insufficient resources available to address the adjustment issue, whereas employing an excessive number of neurons would prolong the training time, while also causing an over fit. According to Ciurana et al. (2008) and Mehrotra (1997), for function approximation, a two-layer neural network is generally enough for an accurate model.

[9]Normally, the number of iterations ranges from 1,000 to 10,000, and a trial-and-error process is recommended (Cabaneros et al., 2019; Yegnanarayana, 2009).

[10]Two extremes should be avoided: too little of a learning rate can cause a significant decrease in the speed of convergence and the possibility of ending up trapped in a local minimum; instead, too high of a learning rate can lead to instabilities in the error function, which will prevent convergence from occurring because jumps around the minimum will be made without reaching it. Therefore, it is recommended to choose a learning rate as large as possible without causing large oscillations (Hassoun, 1995).

TABLE 4 ANN-MLP architecture for the interaction analysis

Simulation	ANN architecture	Activation functions	Percent incorrect predictions (%)	Correlation: output/ predicted output
Internal & new market & governmental drivers/ eco-innovation (t)	6-6-1	• Hyperbolic tangent • SoftMax	• Training: 33.2 • Testing: 33.1 • Holdout: 33.6	.709***

*Error (Cross-entropy).
**Correlation is significant at the .01 level (two-tailed).

value of between 0.05 and 0.5. Finally, the moment factor (α) accelerates the convergence of the weights. Hassoun (1995) and Yegnanarayana (2009) point out that a value close to 1, for example, 0.9, is a good value.

The results of the architecture for the model are shown in Table 4. The structure is 6-6-1, which implies the input, hidden and output layers each have 6, 6 and 1 neurons (respectively).[11] Moreover, a hyperbolic tangent function was used for the hidden layer and a softmax function for the output layer.

The analytical equation of our simulation with ANN-MLP takes the following form:

$$Ecoinnovation = h\left[\sum_{k=1}^{6} \alpha_k \cdot g\left(\sum_{j=1}^{6} \beta_{jk} \cdot X_j\right)\right]$$

with Xj being the input variables;
j the number of input variables;
$h(.)$ and $g(.)$ the hyperbolic tangent and SoftMax activation functions;
αk and βjk the input and hidden network weights, respectively;
k the number of hidden layers.

5.2 | Estimation of the interaction and interdependencies among drivers

Regarding the hypotheses, which suggest the existence of interaction and interdependence between the drivers in the eco-innovation development process, we have tested these through ordinal logistic regression (see Tables 7 and 8), using eco-innovation as dependent variable. As independent variables, we have defined categorical variables, considering each category as a combination of different drivers, using a similar method as Arranz et al. (2019); Ballot et al. (2015); and Mohnen and Roller (2005). Our analysis follows the methodology of the supermodularity framework, based on the seminal work of Milgrom and Roberts (1995) and lattice theory (Topkis, 1998). This approach has been frequently used in the field of innovation when investigating the interactions between innovations, analysing the existence of complementarities (Arranz et al., 2019; Ballot et al., 2015; Doran, 2012; Mohnen and Roller, 2005). This method requires the use of large samples, as is our case with more than 5,000 companies.

[11]The cases utilised to obtain these results were in the training (70.3%), testing (19.7%) and holdout (10.0%) phases.

In Table 7 (Model 5), the independent variable is a categorical variable [ECM ($t-1$); innovation capability ($t-1$); cooperation ($t-1$)]. Thus, we define four categories, considering the possible interactions between the ECM variable, and the innovation capability and cooperation variables. That is, the first category [ECM ($t-1$); 0; 0] is the reference category, which represents the case where a company develops eco-innovation exclusively with ECM, without considering the interaction with innovation capability or cooperation agreements. The second category [ECM ($t-1$); innovation capability ($t-1$); 0] is where ECM interacts with innovation capability; that is, a company developed eco-innovation considering the interaction of ECM with innovation, but not with cooperation agreements. The third category [ECM ($t-1$); 0; cooperation ($t-1$)] corresponds to the interaction between ECM and cooperation, without considering the interaction with innovation. The final category [ECM ($t-1$); innovation capability ($t-1$); cooperation ($t-1$)] is when all the variables interact in the development of eco-innovation. Similarly, in Model 2, the various categories of interactions are represented between innovation capability ($t-1$), ECM ($t-1$) and cooperation ($t-1$), the reference category being innovation capability ($t-1$). Model 3 represents the various categories of combinations of cooperation ($t-1$), with ECM ($t-1$) and innovation capability ($t-1$), the reference category being cooperation ($t-1$). Moreover, in Table 8, following the same methodology, we analyse the marginal effects of market drivers and governmental drivers on internal drivers.

For the analysis of our results, using categorical variables, the various regression coefficients must be interpreted as follows. Model 8, the regression coefficient value 0 reflects the reference category, in which ECM ($t-1$) does not interact with innovation ($t-1$), nor with cooperation agreement ($t-1$). The rest of the regression coefficients obtained correspond to the various categories combining the various variables, which reflect the probability of developing eco-innovation, with respect to the first category. That is, H0: ß ≤ 0 means there is a greater probability of eco-innovating without interaction with other internal drivers, and H1: ß > 0 entails there is a greater probability of eco-innovating with interaction with internal drivers.

6 | RESULTS AND DISCUSSION

Before analysing the results, we have checked the robustness of the questionnaire and responses, testing the common method variance (CMV) and common method bias (CMB), following the method of Podsakoff et al. (2003). These robustness tests show seven latent constructs that represent 60.55% of the variance. The first component is responsible for 19.112% of the variance, which is less than the suggested limit of 50%. Hence, we can confirm that CMV and CMB are not a concern in our analysis.

To measure the direct effect of drivers ($t-1$) on eco-innovation (t), Table 5 displays the results obtained. From the regression analysis, we observe good statistical robustness, since it does not indicate problems of collinearity between variables (none of the VIF values exceeds 2.5), and there are no problems of autocorrelation of residuals with the dependent variable (as shown in the Durbin–Watson value of 2.007) (Hair et al., 1998). However, we do see a low explanatory power of eco-innovation by the independent variables, as no model exceeds 0.4 of the explained variance. The results show that while the internal and government drivers have a positive and significant direct effect on the development of eco-innovation, in line with previous studies (see, e.g., Doran & Ryan, 2016; Frigon et al., 2020; Kiefer et al., 2017), it is observed that there is a variability in the results of the new market variable, not concluding if this variable has a direct effect on eco-innovation. Moreover, from our results, we see an important variability in the regression coefficients, which makes it difficult for us to estimate the quantitative contribution of each independent variable. Additionally, we have checked various regression models (linear, quadratic and cubic) in order to check if another relationship between dependent and independent variables would have a better fit, but the results do not show this (see Appendix A).

Regarding the analysis of the interaction effect, Table 6 shows the results of ANN-MLP analysis in the relationship between drivers ($t-1$) and eco-innovation (t). Concerning the robustness of the analysis, we can indicate that the robustness of the simulation is high, taking into consideration the various tests performed. The first test displays the fitting of the ANN-MLP design. Thus, we see in Table 4 the percentage of incorrect predictions, which assumes that the ANN-MLP architecture has an approximate adjustability of 70%. Moreover, we have analysed the correlation between the actual output variable and the resulting ANN (predicted output) having a high correlation (0.718). The second test has determined the predictability of our models. For this, we have used the ROC curve (receiver operating characteristics), which is a figure that illustrates sensitivity against specificity, displaying the classification performance (Woods & Bowyer, 1997). In our case, the ROC curve shows that the chosen architecture has the capacity to predict more than 70% of the values of the output variable (Figure 4).

Focusing on the results of the simulation of the impact of drivers ($t-1$) on eco-innovation (t), Table 8 displays the normalised importance of the effect of each driver on the firm's eco-innovation (Ibrahim, 2013). This is, following the Garson algorithm (1991), we assess the importance of input variables in an ANN, particularly in the context of an MLP neural network. The algorithm calculates the normalised importance of each input variable based on the weights associated with the connections between the input layer and the hidden layer (or between subsequent hidden layers). The next equation estimates the normalised importance:

$$RI_x = \sum_{x=1}^{n} \frac{|w_{xy}\, w_{yz}|}{\sum_{y=1}^{m} |w_{xy}\, w_{yz}|},$$

where RI_x denotes the relative importance of neuron x.

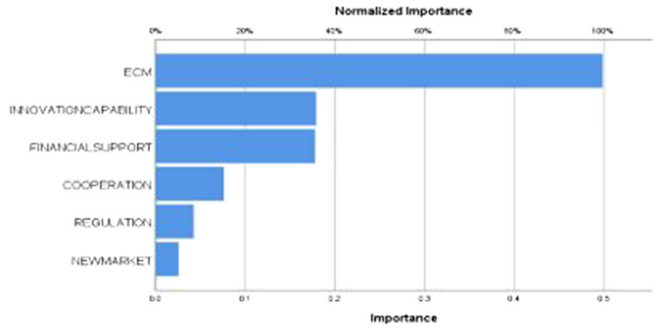
TABLE 5 Direct effect of drivers on eco-innovation

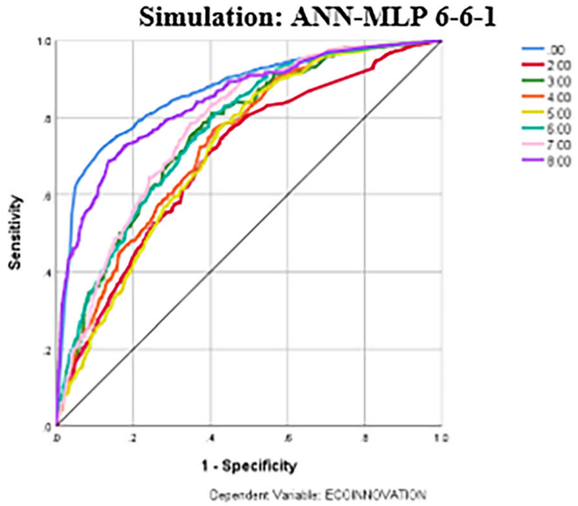
Variables ($t-1$)	Model 1	Model 2	Model 3	Model 4[a]	VIF
ECM	0.516***			0.503***	1.959
Innovation capability	0.492***			0.466***	2.290
Cooperation	0.416***			0.240***	1.408
Financial support		1.400***		0.305***	1.352
Regulation		0.058**		0.048**	1.004
New Market			1.338***	0.058	1.477
−2 log likelihood	2,266.515	751.449	174.076	7,779.529	
dChi-square	3,301.850	1,792.931	585.386	3,364.854	
Sig.	.000	.000	.000	.000	
Cox and Snell	.469	.291	.106	.375	
Nagelkerke	.481	.298	.109	.388	
McFadden	.174	.094	.031	.177	

[a]Durbin–Watson Test: 2.007.
*p < .05.**p < .01.***p < .001.

TABLE 6 ANN-MLP simulation for each of the dependent variables

Variable (*t*−1)	Simulation: Importance	Simulation: Normalised importance (%)
ECM	0.499	100.0
Innovation capability	0.179	35.9
Cooperation	0.076	15.3
Public financial support	0.178	35.7
Regulation	0.042	8.5
New market	0.026	5.2





Area Under the ROC Curve

Values	Area
0	.831
2	.721
3	.768
4	.735
5	.789
6	.782
7	.770
8	.819

FIGURE 4 ROC curve of ANN-MLP. *Note*: the ROC (receiver operating characteristics) curve depicts the classification performance by plotting is a figure sensitivity against specificity. The classification becomes more precise as the curve moves away from 45° line.

$\sum_{y=1}^{m} w_{xy} w_{yz}$ represents the sum of the product of the final weights connections from input neurons to hidden neurons and the connections from hidden neurons to output neurons.

Therefore, in Table 8, we observe that all internal drivers have a positive and significant impact on the development of eco-innovation, but with a differential impact. It is observed that ECM (.499; 100% normalised value), innovation capability (.179; 35.9% normalised value) and cooperation (.076; 15.3% normalised value) have a positive effect. These results contribute to the empirical evidence, corroborating previous studies that show the efficacy of these three drivers in interaction in promoting eco-innovation in a company (see, e.g., Demirel & Kesidou, 2019; Arranz et al., 2020). Moreover, we provide novel empirical evidence of the efficiency of internal drivers in the development of eco-innovation. Thus, we observe that the most efficient is ECM, followed by capability innovation, which in comparison with ECM, its impulse represents only 35.9%, while cooperation agreements represent only 15.3%. Second, in line with previous studies, government drivers are effective in developing eco-innovation (Fischer & Pascucci, 2017; Gallego-Alvarez et al., 2017; Triguero et al., 2013). However, in terms of efficiency, we observe an important disparity between the effect of the existence of public funds (35.7%) and regulation (8.5%). In this aspect, our results provide further evidence to the literature that points out the importance of policies with a direct effect on companies, and actions of a general nature such as regulation (Jové-Llopis & Segarra-Blasco, 2020; Tashman & Rivera, 2016). Finally, we see that the market, in interaction with other drivers, is effective in its impulse in the development of eco-innovation, contributing empirical evidence to the inconclusive results of the literature. Additionally, we must emphasise that in terms of efficiency compared with the other drivers, it has an almost residual impulse (5.2%), which may explain the divergence of results that exist in the literature regarding its effect on eco-innovative development.

Therefore, from our results, we have not only provided empirical evidence of the effectiveness but also of the efficiency of the different drivers, allowing a quantification of the impulse in the development of eco-innovation.

Regarding Hypothesis H1, Table 7 shows the results of the analysis of the marginal effect of interactions between the internal drivers ($t-1$) and their impact on the development of eco-innovation (t). In Model 5, we analyse the impact of ECM on the development of eco-innovation, considering the interaction with the rest of the internal drivers. As a preliminary result, we observe that the interaction between ECM and the rest of the internal drivers is a reinforcing interaction, as a consequence of the positive and significant sign of the regression coefficient. More in detail, the impact of ECM in interaction with cooperation ($\beta = .746$; $p < .001$) is greater than that obtained between ECM and innovation capability ($\beta = .479$; $p < .001$). Moreover, the joint effect of the three internal drivers is superior to the previous interactions ($\beta = .852$; $p < .001$), reflecting the accumulation and reinforcing nature of the interactions. Model 6 shows the results of the interaction of innovation capability with the other internal drivers. Thus, we obtain similar results: innovation capabilities and ECM ($\beta = .486$; $p < .001$), innovation capability with cooperation ($\beta = 1.895$; $p < .001$) and innovation capability with ECM and cooperation simultaneously ($\beta = 2.029$; $p < .001$) have a positive and significant impact. Finally, Model 7 takes the cooperation agreements as a reference, and similarly to previous results, a positive and significant value is obtained in the successive interactions: either with ECM ($\beta = 2.029$; $p < .001$), with innovation capabilities ($\beta = .807$; $p < .001$), or with both ($\beta = 2.343$; $p < .001$). From our results, we can confirm Hypothesis H1, pointing out that there is an effective interaction between the internal drivers and its effect on the development of subsequent eco-innovation.

Regarding Hypotheses H2–H4, in Table 8, we observe the results of the analysis of the marginal effect of interactions between internal drivers ($t-1$) and external drivers ($t-1$) and their impact on the development of eco-innovation (t). In Model 8, we analyse the impact of internal drivers and their effect on eco-innovation, considering the interaction with government drivers. As a result, the interaction between internal drivers and governmental drivers is significant with respect to the impact of internal drivers acting individually, thus being a reinforcing interrelation, as a consequence of the positive and significant sign of the regression coefficient. More in detail, positive coefficients are obtained for the impact of internal drivers in interaction with regulation ($\beta = .229$; $p < .001$), with public financial support ($\beta = .348$; $p < .001$), and with both together ($\beta = .450$; $p < .001$), which indicates that the contribution of external drivers increases the probability of developing eco-innovation in the following period. Furthermore, we see that the function is cumulative and reinforcing since as the number of drivers increases, the probability increases. From our results, we can confirm Hypothesis H2, noting that there is an effective interaction between internal drivers and governmental drivers and its effect on the development of subsequent eco-innovation. In Model 9, we analyse the impact of internal drivers, and their effect on eco-innovation, considering the interaction with the new market driver. As a result, we note that the interaction between internal drivers and the new market is not significant with respect to the impact of internal drivers acting individually. Therefore, we cannot corroborate Hypothesis H3. Finally, Hypothesis H4 is corroborated, as shown by the results of Model 10. In this, we observe that although

TABLE 7 Marginal effect of interactions between the internal drivers and eco-innovation

Variables ($t-1$)	Model 1	Model 2	Model 3
ECM	0		
*ECM*Innovation capability*	0.479***		
*ECM*Cooperation*	0.746**		
*ECM*Innovation capability*Cooperation*	0.852***		
Innovation capability		0	
*Innovation capability*ECM*		0.486***	
*Innovation capability*Cooperation*		1.895***	
*Innovation capability*ECM*Cooperation*		2.046***	
Cooperation			0
*Cooperation*ECM*			2.029***
*Cooperation*Innovation capability*			0.807**
*Cooperation*ECM*Innovation capability*			2.343***
−2 log likelihood	146.454	200.602	135.125
Chi-Square	151.926	528.603	247.503
Sig.	.000	.000	.000
Cox and Snell	.025	.179	.191
Nagelkerke	.025	.183	.195

$^*p < .05$. $^{**}p < .01$. $^{***}p < .001$.

TABLE 8 Marginal effect of interactions between internal drivers and external drivers, and eco-innovation

Variables (*t*−1)	Model 1	Model 2	Model 3
Internal	0		
*Internal*Regulation*	0.229**		
*Internal*Finance support*	0.348**		
*Internal*Regulation*Finance support*	0.450***		
Internal		0	
*Internal*New Market*		0.150	
Internal			0
*Internal*New Market*			0.090
*Internal*Governmental*			0.410***
*Internal*New Market*Governmental*			0.470***
−2 log likelihood	287.611	63.924	126.504
Chi-Square	501.024	1.158	199.577
Sig.	.000	.282	.000
Cox and Snell	.190	.032	.066
Nagelkerke	.193	.032	.068
McFadden	.079	.013	.028

*$p < .05$. **$p < .01$. ***$p < .001$.

it is new for the market, it is not an interaction to reinforce the internal drivers; however, acting jointly with the governmental drivers, we see that there is a reinforcement effect going from ($\beta = .410$; $p < .001$) to a coefficient ($\beta = .470$; $p < .001$).

As discussion of the results, this paper has investigated how internal, governmental and market drivers affect the development of eco-innovation in firms. Thus, from a systems approach, we have modelled the effect of these drivers, considering the existence of interaction between them, and analysing how they, in a dynamic and interactive process, promote the development of eco-innovation in companies. First, we have analysed the direct effect of drivers on the development of eco-innovation. As we have indicated, the direct effect corresponds to the non-consideration of the existence of interaction between the drivers. Our results corroborate previous hypotheses, indicating that both internal drivers and government drivers have a positive effect on the development of eco-innovation. Moreover, the results show, as, in previous studies, variability in the results combined with a low explained variance of eco-innovation (D'Amato et al., 2021; del Río et al., 2016; Doran & Ryan, 2016; Horbach, 2016; Jové-Llopis & Segarra-Blasco, 2020). However, the use of a systems perspective (Bergek et al., 2008), in which the drivers interact with each other in a dynamic process, combined with the use of ANN-MLP, provides us with a higher level of explanation. Thus, compared to the analysis of the direct effect, which explains 30% or 40% of the variance, we see that the analysis of the drivers in interaction provides a model fit greater than 70% of the variance. Therefore, from our modelling, we can derive the following conclusions. On the one hand, the use of regression models with a predetermined relationship (linear, logit, quadratic and cubic) does not provide a good model fit compared with the use of learning algorithms. On the other hand, the need to consider the interaction between various drivers in the modelling. Thus, our hypotheses corroborate how internal drivers and external drivers interact in reinforced feedback, which has a significant effect on the development of eco-innovation compared with the exclusive consideration of the direct effect. Moreover, from the perspective of dynamic capability, our modelling of internal drivers as capabilities of the firm in developing processes is adequate and coherent, with the current point of view that innovation processes interact in companies, producing synergistic and learning effects. In this line, the external drivers have been modelled following NRBV and stakeholder theory, pointing out the need for companies to access external resources and capacities that support the development of eco-innovation.

Second, our modelling allows us to analyse the efficacy of drivers in the development of eco-innovation. Our results corroborate previous research by showing how internal and governmental drivers show their efficacy in the development of eco-innovation (Cai & Zhou, 2014; Doran & Ryan, 2016; Kiefer et al., 2019). Moreover, our results clarify the debate created about the effect of the market on eco-innovation (Horbach et al., 2012; Kesidou & Demirel, 2012; Kiefer et al., 2019). Our findings show, on the one hand, that the exclusive consideration of the direct effect is not conclusive in its efficacy in the development of eco-innovation. Thus, it can be argued that the double externality effect has an important influence on this driver due to the social character of eco-innovation. This means that simply the existence of a market is not attractive enough for companies to develop eco-innovation, with the importance of internal costs prevailing (see, e.g., Arranz et al., 2020). However, if we consider the model in interaction, we observe that the market driver is effective in developing eco-innovation. That is, from the perspective of NRBV and stakeholder theory, internal drivers look for resources and capabilities that reinforce their internal processes. This is the case of the market driver, which provides internal drivers with informative resources that reinforce internal capacities in their development of eco-innovation.

Lastly, our results provide evidence of the efficiency of the different drivers, showing differential levels of these. In the first place, the findings indicate that ECM stands out in its efficiency over the rest of the drivers, as the environmental corporative policy has an important impact on the development of green products (Demirel & Kesidou, 2019; Li et al., 2020; Orazalin, 2020). Shah and Arjoon (2015) and Banerjee (2002) have argued that both the commitment of the management towards environmental sustainability, plus the strategic nature of it in an organisation are the key elements of the development of eco-innovation in a firm. At a second level, we highlight both internal innovation capacities and the existence of external financial resources. The existence of financial resources particularly has been profusely highlighted in the literature as a direct incentive of eco-innovation processes, derived from the tangibility of these resources, having been widely used in the development of innovation policies (see, e.g., Qi et al., 2021). However, the existence of innovation capabilities in a company has been scarcely addressed in the literature. Arranz et al. (2020) have highlighted the parallelism of both processes and the ease of migrating from one to the other. Finally, the findings point out that cooperation, market and regulation drivers are the least efficient in developing eco-innovation. That is, cooperation, as a driver of eco-innovation is more of an operational process of an organisation to gain resources and knowledge than a strategic one. These results are in line with Melander (2018), Horbach (2016) and Niesten et al. (2017). Market drivers, as we have noted previously, are highlighted as informative resources facilitating internal drivers. Finally, regulation appears as a driver, facilitator or incentive for internal processes. In this sense, the literature on institutional theory showed the variability of institutional pressures, from mandatory compliance (coercive measures) to voluntary or recommended use (normative or mimetic) (Arranz et al., 2022; DiMaggio & Powell, 1983). Therefore, it is to be expected that in terms of efficiency, we can find in subsequent studies greater variability, derived from the variability of institutional pressures themselves.

7 | IMPLICATIONS

The findings of this study have several significant implications for academia, business practices, and policymaking. First, from an *academic perspective*, this research enriches the understanding of eco-innovation dynamics by exploring the non-linear interactions among internal, market and governmental drivers. By bridging the gap between theory and real-world complexities, this research refines existing models and develops a new framework that captures the intricate nature of eco-innovation development companies. Moreover, the insights derived from this study offer practical guidance for managers to foster eco-innovation in their companies. Understanding the synergistic effects of different drivers can inform strategic decision-making processes within companies. Firms can prioritise their efforts and allocate resources effectively by focusing on drivers that have a higher impact on eco-innovation. For instance, building on these results, firms would substantially benefit from channelling financial assets and managerial efforts towards enhancing their internal R&D capacities and implementing green management practices, which will help them with the development of impactful eco-innovations. Additionally, the study's emphasis on the systemic interaction between drivers highlights the importance of holistic approaches within organisations, encouraging cross-functional collaboration and knowledge exchange.

Second, this research has implications for policymakers and regulatory bodies. Traditional policy measures have often focused on isolated drivers, overlooking their interconnections. The findings underscore the need for comprehensive and integrated policy frameworks that consider the complex interplay between internal, market and governmental factors. Policymakers can design targeted interventions that facilitate synergies between different drivers. For instance, offering financial incentives for internal innovation while simultaneously creating supportive market conditions can create a conducive environment for eco-innovation to flourish. Additionally, understanding the efficiency levels of various drivers can guide policymakers in prioritising their support, ensuring that limited resources are channelled into the most impactful areas.

Hence, this research contributes to managers and policymakers by clarifying both the effectiveness and efficiency of various drivers in their impulse to develop eco-innovation. First, regarding company managers, this research identifies which factors influence the most the development of eco-innovation. Given the limited resources available to companies, the findings allow for the prioritisation of actions to be performed, as well as increased effectiveness and efficiency in the development of eco-innovation. Second, in terms of environmental policy development, the results highlight the importance of developing effective environmental policies that include not only financial and regulatory support, but also training support programmes and information exchange channels, with the goal of fostering green skills and competencies in the companies, as well as creating incentives to persuade consumers towards the consumption of green products. Furthermore, this research highlights the importance of fostering a culture of collaboration and information exchange between public institutions, businesses, and research organisations. By sharing insights and best practices, stakeholders can collectively work towards sustainable innovation. Initiatives encouraging such collaboration can significantly enhance the eco-innovation landscape, leading to a more sustainable future.

8 | CONCLUSIONS

This study contributes substantively to the eco-innovation literature, shedding light on the intricate processes underpinning eco-innovation development. By embracing a dynamic systems perspective and employing a comprehensive methodological approach, this research advances both theoretical understanding and practical applications in the realm of eco-innovation. As the global pursuit of sustainable practices continues, the insights gleaned from this study serve as a valuable guide for academics, practitioners and policymakers alike, fostering a more eco-innovative future for businesses and society as a whole.

From a *theoretical perspective*, the paper contributes to the existing literature on eco-innovation by modelling eco-innovation as a dynamic and interactive process, which enhances the knowledge of how eco-innovation is developing. While NRBV and the stakeholder perspective emphasise that a company's internal resources, combined with the need to establish relationships with other external agents, are the determining factors for the development of eco-innovation, our contribution, from a systems approach, expands the understanding of how these factors affect the development of eco-innovation. Hence, we indicate the need to study eco-innovation from the theory of dynamic systems, considering that the result of eco-innovation not only depends on the existing drivers but also on how these interact in a dynamic and non-linear process.

From a *methodological perspective*, the research contributes to a deeper comprehension of the processes, factors and interactions that affect the development of eco-innovation. Unlike previous studies (Olden et al., 2004; Triguero et al., 2013; Yu et al., 2019) that have fundamentally analysed the direct effect that influenced the external perspective of the relationship between drivers and eco-innovation, we consider the need to combine classical econometric methods with approaches from machine learning, which allow us a greater degree of understanding and explanatory power of how drivers affect eco-innovation in companies.

Finally, this research is not without limitations. Although the research employed a large and robust sample, future research could broaden the results expanding the sample to different geographical contexts. Additionally, while the Community Innovation Survey was utilised as a robust questionnaire, future research could explore other alternative variables to further validate the results. Furthermore, this study specifically focuses on the generation of eco-innovation and not on its adoption. While different mechanisms may be at play for the generation and adoption of eco-innovation, this study only examines the factors that drive the generation of eco-innovation. Despite these limitations, the results of this study contribute to the literature on eco-innovation and provide insight into the factors that drive the development of eco-innovation in firms.

ORCID

Carlos F. A. Arranz https://orcid.org/0000-0002-6866-0684

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APPENDIX A: LINEAR, QUADRATIC AND CUBIC REGRESSION ANALYSIS

Model summary and parameter estimates					
Dependent variable: ECOINNOVATION					
		Model summary		Parameter estimates	
Variables	Equation	R square	Sig.	Constant	β
ECM	Linear	.433	.000	0.563	0.683
	Quadratic	.434	.000	0.473	0.806
	Cubic	.435	.000	0.424	1.081
Innovation capabilities	Linear	.290	.000	1.216	1.883
	Quadratic	.295	.000	1.085	2.771
	Cubic	.295	.000	1.085	2.472
Cooperation	Linear	.129	.000	2.409	2.394
	Quadratic	.129	.000	2.409	2.394
	Cubic	.129	.000	2.409	2.394
Financial support	Linear	.132	.000	2.422	1.585
	Quadratic	.147	.000	2.329	2.898
	Cubic	.148	.000	2.322	3.567
Regulation	Linear	.112	.000	2.866	0.127
	Quadratic	.112	.000	2.836	0.272
	Cubic	.112	.000	2.830	0.403
New Market	Linear	.004	.000	2.421	2.172
	Quadratic	.005	.000	2.421	2.172
	Cubic	.005	.000	2.421	2.172