How do internal, market and institutional factors affect the development of eco-innovation in firms?

Abstract

This paper investigates how drivers affect the development of eco-innovation in firms. Our research classifies the eco-innovation drivers in three categories: *internal factors, market factors, and institutional factors*. Using a sample with 9,172 firms from the Spanish Innovation Survey Panel, we study the impact of eco-innovation drivers for energy and environmental efficiency objectives. This research utilizes a combination of two methods: Ordinal Logit Regression Models and Artificial Neural Networks. The results allow us to compare the impact of each variable. From a methodological point of view, this approach allows overcoming the difficulties of performing a regression analysis, mainly due to the low levels of explained variance and the problem of comparing the regression coefficients obtained. From the Artificial Neural Networks analysis, it is observed that the factor that most affects the eco-innovation is the previous experiences in eco-innovation, compared to variables such as external financing or innovation capabilities, which have a very small impact. These results may have important repercussions from the point of view of developing environmental incentive policies.

Keywords: *Eco-innovation, Drivers, Methodological Approach; Regression; Artificial Neural Networks*

1. Introduction

Eco-innovation is becoming a common and essential innovative strategy in companies (Ch'ng, et al., 2021; Yang et al., 2020; Frigon et al., 2020; Baldassarre et al., 2019; Arranz et al., 2020). Dangelico et al. (2017), and Arranz et al. (2019), highlight that companies develop eco-innovation with the purpose of seeking a sustainable economy. Examples of these eco-innovation activities are the implementation of circular economy models (Pieroni et al., 2019; Geissdoerfer et al, 2018). Companies innovate in closed-loop production strategies, following the 3Rs principles (*reduce, reuse, and recycle*) (see, for example, Rosa et al., 2019). Moreover, companies innovate in the adaptation and implementation of the Directive 2009/125/EC, as well as ISO 9001, 14001, and

Integrated Management Systems. This means changes in the product, process, and organizational structure of the firm (Arranz et al., 2019; Evans et al., 2017; Bocken et al., 2014). In fact, in the Lisbon strategy goals for competitiveness and economic growth, the European Parliament considered eco-innovation the most contributing factor for sustainable development (Rodriguez et al., 2010). Likewise, Kijek and Kasztelan (2013) and Lee et al. (2018) reveal how eco-innovation has become a differentiating attribute for sustainable enterprises, representing a solution for development problems. By enabling partial replacement of material inputs with knowledge capital, this allows firms and entire economies to become more efficient and effective.

In this context, different lines of research have intended to investigate the drivers of eco-innovation from a firm-level perspective (Bonzanini et al., 2016; Melander, 2018). Several theoretical approaches have recognized three categories of eco-innovation drivers in all firms: *demand-side, internal and regulatory and policy side drivers* (Horbach, 2008; Triebswetter and Wackerbauer, 2008; Horbach, Rammer and Rennings, 2012; Del Rio, Peñasco and Romero-Jordan, 2016; Qi et al., 2021). Although these works have made important contributions to explain the factors *which* affect the development of eco-innovation in all firms, *how* they affected has been scarcely analysed and with inconclusive results (Fischer and Pascucci, 2017; Zubeltzu-Jaka et al., 2018; Kiefer et al., 2019).

Existing literature about eco-innovation drivers has only applied simple regression models for their study (Jové-Llopis and Segarra-Blasco, 2020; Cai and Zhou, 2014; Kesidou and Demirel, 2012). Nevertheless, most regression models do not perfectly fit the available data and cannot estimate the underlying function of the data because of the intricacy of the real system. That is, in addition to the classic assumptions of regression models, both the collinearity problems and the low explanatory power of these models should be considered (Setiono and Thong, 2004). Moreover, sustainability literature remarks on the importance of considering the interdependency and the interactions between these factors that have an effect on eco-innovation (Arranz et al., 2019; Bossle et al., 2016; Doran and Ryan, 2016; Horbach et al., 2012). In a company, eco-innovation does not happen only as a direct result of every single factor. Internal factors, such as experience and innovation capability need to be complemented with internal and external economic resources to innovate. Similarly, regulations and the demand for eco-innovation have an impact on the internal factors of the firm. There is always an interdependency between predictor variables in real-life innovation that regression models are not able to identify. Arranz et al. (2020)

point out that to have a complete overview of how drivers impulse the eco-innovation in firms, it is not only necessary to know *What* factors, but *How* they impact, which drivers are more important, and if there are interactions and complementarities between the different drivers.

In our study, we assume a methodological approach to test the following research question: *how do the drivers affect the development of eco-innovation in firms?* To answer this, firstly, our research classifies the eco-innovation drivers in three categories: *internal factors, market factors, and institutional factors*. The paper study the impact of eco-innovation drivers for energy and environmental efficiency objectives as well as the sum of both eco-innovation objectives. The data is retrieved from PITEC (Spanish Innovation Survey Panel), which includes 9,172 firms. Moreover, to avoid methodological problems, this research utilises a combination of two methods: Ordinal Logit Regression Models and Artificial Neural Networks (ANN). ANNs are a good complementary method to identify precisely the underlying function of any data. The ANN, compared to other prediction methods, allow us to analyse complex problems (for example non-linear relations), determining all interactions among the predictor and output variables, through multiple training algorithms.

2. Conceptual Framework and Model

In the literature, eco-innovation relates to new products, processes, services, and/or organizational changes that help in reducing the use of earth's resources, and at the same time diminishes the harmful substances through its lifecycle (EIO, 2013). Moreover, Arranz et al. (2020) describe eco-innovation as a form of innovation, with the purpose of the reduction of pollution and the seeking of a sustainable economy. In this line, Dangelico et al. (2017), and Bossle et al. (2016) classify the objectives of eco-innovation as reducing the environmental impact of the company's activities, complying with environmental regulatory requirements, and in greater energy savings.

In our model, we proposed which factors or drivers affect the development of eco-innovation in industrial firms and how they affect the company. We assumed the hypothesis of variability in the behaviour of the companies to develop eco-innovation. This means that not all companies are affected in the same way by the same factors. In this context, firms establish eco-innovation objectives as a result of combining external pressures (government and market) with internal voluntary and proactive eco-innovation (Jové-Llopis, and Segarra-Blasco, 2018; Doran and Ryan, 2016). Thus, it is observed that the firms have variability in their strategy behaviour, which means that we can find a variety of scope and degree of eco-innovation implementation. From a passivity in environmental actions, complying exclusively with government requirements; to a proactive position, responding to the demand for green products for new markets. This variety in the level of firms' eco-innovation requires a statistical study of the companies, omitting those coercive actions, which are mandatory for the firms to develop such innovations.

Regarding the drivers of eco-innovation, previous research has focused on the impact that government policies and incentives have on the decision to eco-innovate (Fischer and Pascucci, 2017). In fact, the institutional incentives and rules encourage a firm to develop eco-innovations (e.g., Gallego-Alvarez et al., 2017)[1]. From an institutional approach, there have been developed diverse institutional actions to promote the development of a sustainable economy. Most of these actions have an incentive component, based on *financial facilitators* (Arranz et al., 2019; Kiefer et al., 2017). Eco-innovation requires companies to finance the cost of innovation and product launch. For this, companies must access external sources of financial resources. In this context, institutions and governments, in the various institutional settings, have developed financial mechanisms for the innovation and eco-innovation for the firms (Arranz et al., 2019; Doran and Ryan, 2016; Bonzanini et al., 2016). Therefore, it can be affirmed that the existence of financial supports should facilitate the process of eco-innovations, which will have a positive effect on firms' decisions for eco-innovations.

Secondly, the literature has examined the internal factors of companies to decide to eco-innovate (Fernando et al., 2019; Zubeltzu-Jaka et al., 2018; Bossle et al., 2016; Neto et al., 2014). Arranz et al. (2019), and Tsai and Liao (2017) have settled that decision to innovate in a firm is based on its *innovative capabilities* and its *innovative experience*. From the Dynamic Capability Perspective, Cohen and Levinthal (1990) proposed the notion of innovation capabilities, as the organizational routines and processes which aim to achieve innovation for the company as their final objective (Annunziata et al., 2018; Demirel and Kesidou, 2019). Therefore, the greater the innovation capability in the firm, the greater the probability to innovate. In the second place, the *experience* in previous processes of eco-innovation has a high impact on continuing to eco-

[1] This institutional theory emphasizes that organizations are influenced by the environment, and that their behaviour is defined by rules, constraints, structures, social expectations and common cognitions. The firms change their behaviours and structures, adopting dominant practices to conform to the external environment and institutional environment (DiMaggio & Powell, 1983).

innovate. From a Knowledge Exchange Perspective, innovation is considered as a knowledge in the firm that must be managed (Arranz et al., 2020). In this context, innovative development is conceptualized as a process of knowledge management and learning (organizational learning), considering it as a cumulative learning process. Thus, the experience is justified as a driver of innovation as a consequence of the need for previous knowledge that is necessary for this innovative development. Moreover, Arranz et al. (2020) point out that the experience generates learning and economies of scale in the development of innovation processes. Therefore, it is expected that firms might implement objectives of eco-innovation based on the level of the company's innovative capabilities and previous experiences.

As the last factor in the developing eco-innovation, we find the pull factor of the market. As it is well known, demand fosters innovative development in organizations (Amui et al., 2017; Chang et al., 2015). This has been emphasized prominently in the market of sustainable products. The proactive attitude of the consumer towards the consumption of ecological products has served as an incentive for new product development (Zhang, et al., 2020; Demirel and Kesidou, 2019) or the incorporation of new companies in these sectors (Annunziata et al., 2018; Arranz et al., 2020). In addition to this pull effect by the market, companies in their process of innovation, create portfolios of products and services, in which sustainable products and services are introduced every day. Therefore, it is expected that the *pull/push effect of the market* might have a significant and positive influence on eco-innovation in firms.

In Table 1, we summarise the research model. Moreover, this model would not be complete without considering the interaction of these factors and their impact on eco-innovation. From the methodological point of view, the direct effect of each of the variables on eco-innovative development has been considered. This direct effect has been analysed with the regression model (see Figure 1). However, to truly understand the situation, one must consider the coexistence of the three types of factors (institutional, internal, market), which interact with each other before considering their effect on the decision to eco-innovate. Namely, experience affects innovation capability, creating prior knowledge, which should have a positive effect on previous innovation capabilities in firms. In addition, the existence of financing has a significant impulse on the innovation capacities of companies. A firm considers the capabilities, not only as of the development of innovation processes but also the existence of financing, which predisposes the company to a greater probability of developing eco-innovation. Therefore, to understand how the various factors affect firms, we must analyze its direct effect and its indirect effect, or the effect of their interaction with other factors.

3. Methodology

3.1. Sample

For our investigation, we employ as a database the Spanish Technological Innovation Panel (PITEC) which is the Spanish source of the EU Community Innovation Survey. Table 2, displays the key characteristics and content of PITEC. The reference periods for this study are 2010- 11 (t-1) and 2012-13 (t). The final sample consists of 9,172 firms, about 8,610 of which have established some form of eco-innovation in the 2012-13 period.

3.2 Measures

Dependent variables

The dependent variables correspond to the period of study 2012-13 (t). The survey by PITEC measures eco-innovation of the organization throughout two objectives related to the level of innovative activity oriented to consume less energy per unit (*energy eco-innovation*) and to produce less environmental impact (*environmental eco-innovation*). Each of these objectives is measured as a Likert scale, where the value 1 corresponds to a null level of eco-innovation activities, 2 to a low level, 3 to an intermediate level, and 4 to a high level. Moreover, to have a complete vision of how companies develop eco-innovation and in line with Arranz et al. (2019), we created a third dependent variable (*eco-innovation*) as a result of the sum of the two dependent variables, which better measures eco-innovation diversity and intensity[2] in the firm.

Independent variables

All independent variables correspond to the period 2010-11 (t-1). For the study, the independent variables are classified into three types of drivers: *internal drivers, market drivers, and institutional drivers.*

[2] We have tested whether the variable generated as the sum of the eco-innovation variables, in addition to diversity, measures the intensity of dependent variable (eco-innovation). For this, we have carried out a Factor Analysis with rotation Varimax. The results show one factor for the four variables, explaining 89.770% of the variance (KMO = .825, sig = .000). Then, we compare this variable and that generated as the sum variable through the analysis of the correlation of variables, getting a high correlation (0.901) between the two variables.

This research uses two variables to analyse *internal drivers*. Firstly, the experience of the firm in eco-innovation (*experience*) is measured by the developed and the implementation of eco-innovation in the previous year. If the studied variable is consuming less energy per unit *(energy experience*), the measure of experience corresponds to the energy efficiency variable of the previous year. If the studied variable is producing less environmental impact (*environmental experience*), the measure of experience corresponds to the environmental efficiency variable of the previous year. Secondly, PITEC measures the development of innovation in a firm by identifying if the company implements these four typologies of innovation: product, process, organizational, and marketing innovation. Each category has more sub-categories of innovation. All of them are measured by a dummy variable (0 to 1) if the firm does not develop/develops this innovation. For measuring the capability of innovation of the firm (*innovation capability*) we sum all the subcategories of all types of innovation developed by the firm.

For analysing the *market drivers*, we choose two variables: *new products to the market* and *new products to the firm*. Both of them are measured as a percentage of the firm's revenue that was new to the market (*New market*) or new to the firm (*New firm*).

Finally, for studying the institutional drivers, *public financial support* is the variable included in this research. PITEC classifies external funding in three institutional levels: i) from the local/regional institutions; ii) from the national institutions; iii) from the European Union. Each level is defined as a dummy variable whose value is 1 if the firm receives funding and 0 if not. We measure the level of public funding (*public financial support*) by the sum of the three levels of financial support.

As control variables, we used three features of the firm: *size, belonging to a group, and belonging to the manufacturing or service sector* (Table 3).

3.3. Econometric Model

As indicated before, the purpose of our research is to measure the *direct effect* as well as the *interaction effect* of the factors that have an incidence in the eco-innovation of the company. For the first case, we are going to analyse the direct effect through regression analysis, and for the second case, we are going to implement ANNs.

3.3.1. Regression Analysis: Estimation Models

As for the estimation of the direct effect, we have done it through the Ordinal Logit Regression model, since the dependent variable is ordinal. In fact, the dependent variable is formed with the sum of the variables *energy eco-innovation (t)* and *environmental eco-innovation (t)*, which makes the variable *eco-innovation (t)* has an ordinal scale from 2 to 8. This type of dependent variable limits the use of another type of regression, such as linear, since it does not meet the variance distribution assumptions of linear regression (Hair et al., 1998). In the analysis, we have estimated three models, and the results can be seen in Table 7.

Model 1:

Energy eco-innovation (t) = constant + $ß_1$(*Public financial support* (t-1)) + $ß_2$(*Innovation capability* (t-1)) + $ß_3$(*New market* (t-1)) + $ß_4$(*New firm* (t-1)) + $ß_5$(*Energy experience* (t-1)) + $ß_6$ (*Environmental experience* (t-1)) + $ß_7$(*Group*) + $ß_8$(*Size*) + $ß_9$(*Manufacturing/Service*)+ e

Model 2:

Environmental eco-innovation (t) = constant + $ß_1$(*Public financial support* (t-1)) + $ß_2$(*Innovation capability* (t-1)) + $ß_3$(*New market* (t-1)) + $ß_4$(*New firm* (t-1)) + $ß_5$(*Energy experience* (t-1)) + $ß_6$(*Environmental experience* (t-1)) + $ß_7$(*Group*) + $ß_8$(*Size*) + $ß_9$(*Manufacturing/Service*)+ e

Model 3:

Eco-innovation (t) = constant + $ß_1$(*Public financial support* (t-1)) + $ß_2$(*Innovation capability* (t-1)) + $ß_3$(*New market* (t-1)) + $ß_4$(*New firm* (t-1)) + $ß_5$(*Energy experience* (t-1)) + $ß_6$(*Environmental experience* (t-1)) + $ß_7$(*Group*) + $ß_8$(*Size*) + $ß_9$(*Manufacturing/Service*)+ e

3.3.2. ANN: Procedure and Design.

For the analysis of the effect and interaction of the drives on the eco-innovation variable, we have used an artificial neural network (ANN). This statistical model mimics biological neural networks (the human brain particularly) to model complex patterns and prediction problems, allowing the analysis and prediction of complex relationships (non-linear and multiple-interactions) in causal studies (Pasini, 2015). The ANNs are models that employ parallel information-processing structures for interpreting outcomes. At the same time, they are capable of adjusting their framework to increase the reliability of the model (Zou et al., 2009; Somers and Casal, 2009). For the ANN design procedure, we propose five steps to design the ANN architecture, following the works of Wang (2007) and Ciurana et al. (2008), as can be seen in Table 4.

Regarding the typology of ANN, for this application, we have used the Multilayer Perceptron (MLP) (Figure 2). ANN-MLP is known as a supervised network in the sense that the predicted results can be compared against known values of the dependent variables. The network architecture of an MLP has an input layer, which receives external information, a hidden layer (there can be more than 1), and an output layer. The layers are connected, with their associated weights to the neurons of the hidden and the output layers. Moreover, as a learning algorithm, we will use *Backpropagation*, using a propagation-adaptation cycle of errors and coefficients[3] (Hirose et al., 1991), allowing us to obtain explanatory capacities far superior to other statistical methods. Therefore, the use of learning algorithms in ANNs, makes their application very suitable for prediction problems, interaction problems and non-linear relationships.

Conversely, the use of other analysis methods, such as regression analysis or structural equations, has been discouraged for this type of analysis compared to ANN analysis (Somers and Casal, 2009; Minbashian et al., 2010). Regression models have a limited capacity to explain non-linear patterns between independent and dependent variables, especially when these are in interaction and the relationship pattern is unknown[4]. This occurs, since its optimization algorithms adjust to a line, in the case of linear regression (OLS), or to a sigmoidal function, in the case of the logit model, without having the ability to adapt to different non-linear behaviours. Moreover, the use of regression for the analysis of the interaction involves the analysis of the moderating effect between independent variables, which raises two important limitations. First, Holland et al. (2017) highlight that in a moderation analysis, the joint variable obtains a lower variance than that obtained with the independent variables, which is the first limitation in its explanatory capacity.

[3] Simplified, the operation of the learning algorithm is: First, an input pattern is applied as a stimulus to the first layer of neurons in the network. This stimulus is propagated through all the layers until generating an output. The result obtained in the output neurons are compared with the desired output and an error value is calculated for each output neuron. These errors are then transmitted backwards, starting from the output layer, to all the neurons of the intermediate layer that contribute directly to the output, receiving the percentage of error approximated to the participation of the intermediate neuron in the original output. This process is repeated layer by layer, until all the neurons in the network have received an error that describes their contribution relative to the total error. Based on the value of the received error, the connection weights of each neuron are readjusted, so that the next time the same pattern occurs, the output is closer to the desired one.

[4] Following Minbashian et al. (2010), it is possible to develop regression equations that have the same representation capabilities as neural networks simply by adding a large enough number of power and product terms. However, when the goal is to perform exploratory analyses that make few a priori assumptions about the specific form of non-linearity or configuration, the use of regression analysis is less efficient than ANN analysis.

Second, the moderation analysis may have collinearity problems between the moderating variable (*variable1 * variable2*) and the variables treated independently, *variable 1* and *variable 2*, as a consequence of certain biases that can occur in the samples of companies[5]. On the other hand, the use of structural equation models also has limitations in its explanatory capacity for non-linear and interaction processes (Minbashian et al., 2010). First, the structural equation model uses a linear regression model for causal analysis, introducing previous limitations of linear regression analysis. Second, as a consequence of the interaction analysis being carried out in two stages (the first, latent variables are created with the independent variables and the second the effect of the latent variables on the dependent variable is analysed); in this process, the creation of the construct and the subsequent regression analysis, produces a loss of explanatory capacity[6].

Regarding the design of the ANN architecture for the analysis, we have established the following models considering the different output variables. In terms of time, we established output variables *in period t* (2012-2013), and the input variables in previous periods (2010-11).

Model 1:

Energy eco-innovation (t) *= f(Public financial support* (t-1)*; Innovation capability* (t-1)*; Energy experience* (t-1)*; Environmental experience* (t-1)*; New market* (t-1)*; New firm* (t-1)*)*

Model 2:

Environmental eco-innovation (t) = f(public financial support (t-1); Innovation Capability (t-1); Energy experience (t-1); Environmental experience (t-1); New market (t-1); New firm (t-1))

Model 3:

Eco-innovation diversity (t) = f(public financial support (t-1); Innovation Capability (t-1); Energy experience (t-1); Environmental experience (t-1); New market (t-1); New firm (t-1))

[5] That is, when variables 1 and 2 correspond to company behaviors or strategies, Arranz et al. (2019) point out that normally both behaviors or strategies occur simultaneously in the same company, which means that the variables can be correlated.

[6] Typically, in a moderation analysis, we first create a latent variable, with factor analysis, for example. Each independent variable requires that at least contributes to the new factor with a variance greater than 0.6 (Hair, 1989), having a first loss of variance. The second loss of variance comes from the regression analysis; a good analysis can achieve a R^2 of 0.4. Therefore, considering the two analyses, the model will have a total capacity to explain the interaction by combining both variances, that is, 0.6 * 0.4 = 0.24 (24% of the variance).

Following Wang (2007), and Arranz and Fernandez de Arroyabe (2010), this paper used a *trial and error procedure*. This is, the selected architectures are tested with diverse activation functions, finding that the best architecture is that minimizes the error (Wang, 2007; Arranz and Fernandez de Arroyabe, 2010). The results of the three architectures for the three models are shown in Table 5. For example, for Model 1, the structure is 6-5-1, which means that there are 6, 5, and 1 neuron in the input, hidden and output layers, with hyperbolic tangent and softmax as activation functions[7]. In the case of the hidden layer, the activation function was the hyperbolic tangent and the softmax function for the output layer.

4. Results and Discussion

In this paper, we analyze *how internal and external drivers affect the development of eco-innovation*, performing two types of analysis. First, we have analyzed the direct effect of the variables, through regression analysis. Second, we have considered that the drivers are in interaction, using ANN-MLP to analyse their effect on the development of eco-innovation.

Regarding the direct effect of the drivers on the further development of eco-innovation, Table 7 shows the results of the analysis. Previously, we have also checked the robustness of our methods and results. First, we have checked the common method bias, following Podsakoff et al.'s method (2003). This analysis shows eight distinct constructs that explaining 91.04% of the variance. The first factor only explains 19.09% of the variance[8]. This confirms that, in our findings, the common method bias is not an issue. Second, we have checked for possible collinearity in our results. Table 6 shows the correlations among variables used in the regression analysis. Moreover, Table 7 displays the results of the reliability and robustness of the models, obtaining acceptable values for both the VIF and Durbin-Watson tests.

Model 3 (Table 7) displays the impact of independent variables on eco-innovation. More in detail, we first find that energy experience ($ß = .757$, $p < 0.001$) and environmental experience ($ß = .701$, $p < 0.001$) have a significant and positive impact on eco-innovation. This result contributes to empirical evidence, showing the positive impulse of previous experiences in eco-innovation to facilitate and encourage further eco-innovation. Moreover, this outcome corroborates previous work (for example, Arranz et al., 2019), which show the cumulative character of eco-innovation,

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[7] To obtain these results, the cases were used in the training phases (70.3%), testing (19.7%) and holdout (10.0%).
[8] This is under the suggested 50% threshold.

pointing out that prior knowledge and learning facilitates the subsequent eco-innovation. Secondly, the findings show that the possession of innovation capabilities (ß = .125, $p < 0.001$) also has a positive impulse on eco-innovation. Our results are consistent with previous evidence, which indicates the positive effect that innovation capabilities have on eco-innovation (Demirel and Kesidou, 2019). In line with Arranz et al. (2020), these findings show the parallelism and complementarity between the capabilities of innovation and eco-innovation, providing new empirical evidence to the debate on the relationship between innovation and eco-innovation. Thirdly, it is observed that external financing from institutions and organizations have a positive impulse (ß = .117, $p < 0.005$) on eco-innovation. The results confirm previous findings that indicate the importance of external financing in eco-innovation (Arranz et al., 2020). Finally, our results show that neither the novelty for the market nor the eco-innovation companies have a significant impulse on eco-innovation. These outcomes are in line with prior research, which indicates that eco-innovations imply additional costs for private companies (Arranz et al., 2019; Evans et al., 2017; Borghesi et al., 2015). While eco-innovation reduces social costs (for example, reduction of pollution), this implies investment and higher costs for companies (Arranz et al., 2019; Tang et al., 2018; Dangelico, 2016), resulting in a scarcity of incentives to invest in eco-innovation (De Marchi, 2012). Additionally, if we consider the results for energy eco-innovation, as for environmental eco-innovation, it is observed that the results of the regression models are similar. This can be explained since the eco-innovation variable was created as the sum of both eco-innovation variables and the level of correlation of both variables is high (0.601, $p < 0.005$). This shows that both energy and environmental eco-innovation are perceived in a similar way and understanding that the development of eco-innovation means both energy savings and reduced environmental impact.

Regarding the effects of the interaction of drivers in the development of eco-innovation, Table 8 shows the results of the analysis with ANN-MLP. The robustness of the model is high considering both the error (which in the training stage is .573, and in the testing stage is .507) and the correlation of the actual output variable with the resulting ANN (predicted output) which has a high correlation of .650. The predictability of our three models is also displayed. The chosen architecture can predict more than 70% of the output variable values. This is corroborated by the

ROC curve[9], which represents an area greater than 70% (Figure 3). We can therefore conclude that the ability to predict the three prosed models is good[10].

Focusing on the variable eco-innovation, Table 8 shows the normalized importance of the effect of each input or independent variable in the eco-innovation developed by the firm. It is observed that in line with the previous results showed in the regression analysis, both experiences in energy saving (.438; 100% normalized value) and diminution of environmental impact (.427; 97.6% normalized value) have a positive effect on the variable output. Similarly, external financing (.049; 11.1% normalized value) and innovation capability (.040; 9.1% normalized value) have a positive effect, as the results of the regression model showed. However, unlike the regression models, in the ANN analysis, both novelties for the market (.022; 5.1% normalized value) and novelty for the company (.024; 5.4% normalized value) have a significant and positive effect in eco-innovative development. This may be due to the use of a different methodological model. Just as the regression model poses the direct effect, the ANN-MLP model poses the interaction effect. That is, while the direct effect has no significance in eco-innovation, the effect of the interaction between the variables does. In other words, previous experiences of both eco-innovation and innovation, the position of external financing, plus the novelty for the market, supposes a set of significant variables for the eco-innovation in firms.

Finally, our results allow us to compare the impact of each variable. From a methodological approach, it is problematic to perform a regression analysis, mainly due to the low explained variance and the difficulty of comparing the regression coefficients obtained. From the ANN-MLP analysis, it is observed that the factor that most affects the three eco-innovations are the previous experiences in eco-innovation, which compared with variables such as external financing or innovation capabilities have a very small impact. These results may have important consequences from the point of view of developing environmental incentive policies. Moreover, as shown in the regression analysis, the results for both the eco-innovation variables (energy and environmental eco-innovation) are similar.

The results of our analyses allow us to explain how the drivers affect the development of eco-innovation, and allow us to obtain important contributions both methodological and theoretical,

[9] The ROC (Receiver Operating Characteristics) curve is a figure of sensitivity versus specificity, showing the classification performance. The more the curve moves away the 45-degree, the more accurate is the classification.

[10] This allows us to confirm, in line with the literature, that ANN has a better fit than the regression models, which exceptionally come to explain more than 40% of the variance.

and implications for management. First, from a theoretical point of view, our results show that considering exclusively the direct effect of the variables limits the explanatory capacity of how drives affect the development of eco-innovation. Unlike previous works (Horbach et al., 2012; Cai and Zhou, 2014; Bossle et al., 2016; del Rio et al., 2016; Fischer and Pascucci, 2017; Arranz et al., 2020), our results suggest that adequate modelling must consider the mutual interactions between drivers. According to Sterman (2000), we can conceptualize the interaction between drivers as a dynamic process of mutual feedback between variables, which affects the variables by reinforcing them in the case of positive interactions or weakening them when the interactions are negative. Therefore, the consideration that there is an interaction between the drivers in the development of eco-innovations allows us to take into account the mutual and positive effects between them, which has a significant effect on the subsequent development of the eco-innovation.

Secondly, from the methodological point of view, the use of machine learning methods such as ANN allows obtaining a greater explanatory power in terms of prediction than the regression model, which is in line with previous works in the field of ecological modelling (Olden et al., 2004). It is observed that both the ROC curve, as well as the prediction of error and the correlation between the real and expected output variables, show explanatory values close to 70%, while the regression analysis does not exceed 40% (excluding control variables) of the explained variance. Moreover, although in our study we did not find collinearity problems between variables, the use of ANN allows to overcome this type of concern that affects the quantification of the impact of each variable. In contrast to previous findings (Arranz et al., 2020; del Rio et al., 2016), our results allow to point out that using ANN, we can not only see the degree of significance of the variables but also obtain a greater explanatory power that facilitates to establish a ranking of the impact of the various variables.

Finally, our results offer important implications for managers and policymakers. Derived from the greater accuracy of our analysis, the results allow us to know how each factor affects the development of eco-innovation. Thus, the results provide empirical evidence that past eco-innovations have greater importance in the development of subsequent eco-innovations. These results contribute to the debate on which factors are most critical in the development of eco-innovation (see, for example, Arranz et al., 2020; Del Río et al., 2016). Also, our outcomes are in line with Demirel and Kesidou (2019) and show that the possession of green competencies, as a result of previous experiences in eco-innovation, has a greater incidence than other factors, such as innovation capabilities (Arranz et al., 2020; Annunziata et al., 2018) or regulations (Doran and Ryan, 2016; Del Rio et al., 2016; Horbach et al., 2012). In addition, from the point of view of environmental policies, our results relativize the importance of factors such as public subsidies (Horbach et al., 2012), or market factors (Elmagrhi et al., 2019) compared to the experience in eco-innovation.

5. Conclusion

This paper has investigated how drivers affect the development of eco-innovation in firms. Classifying the eco-innovation drivers in three categories: internal factors, market factors, and institutional factors and using panel data from the Spanish Innovation Survey, we have studied the impact of eco-innovation drivers on energy and environmental efficiency objectives. The paper has three important contributions, the first is a theoretical contribution, framed in the field of environmental literature; the second is a methodological contribution, and the last offer important implications for the management.

As a *theoretical contribution*, our research contributes to the extant literature on environmental innovation and improves our understanding of it. While prior eco-innovation research and environmental theories have focused on identifying the drivers of eco-innovation from a multilevel framework, our research underlines the synergies between these drivers and their influence on ecological innovation in companies. From natural resource-based view theory (NRBV), an extension of RBV theory, not only is emphasized the role of firms' (internal) resources and capabilities as a driver of the eco-innovation but also the stakeholder engagement as a driver for product stewardship and pollution prevention (Hart and Dowell, 2011; Katsikeas et al., 2016; Roxas et al., 2017; Zhang and Walton, 2017). Our contribution, based on pull and push factors, and regulatory and policy side drivers, show how they affected the development of eco-innovation in firms. The most remarkable conclusion is that drivers produce feedback between them and that is necessary to consider in the analysis of the existence of this interaction. This perspective allows a more realistic approach to the effect that drivers produce in the development of eco-innovation in the firm.

From a *methodological approach*, our paper contributes to a better understanding of the processes that affect the development of eco-innovation (Yu et al., 2019; Triguero et al., 2013; Olden et al., 2004). Using machine learning methods, we have postulated that the eco-innovation development process in firms is the result of the interaction between the various drivers. This implies that the use of regression analysis models is limited to understand the process, and that is necessary to introduce methods that allow, on the one hand, the analysis of multiple interactions, and on the other hand, learning algorithms to obtain greater accuracy in estimations.

Finally, from the point of view of *implications for the management*, our contribution is twofold. On the one hand, from the point of view of the managers of the companies, we identified which factors influence the impulse of eco-innovation. Considering the limited resources of firms, this will allow prioritizing the actions to be carried out to increase the effectiveness and efficiency in the development of eco-innovation. On the other hand, from the point of view of environmental policy development, our research highlight the need to develop comprehensive policies, which not only take into account financial and regulatory support, but also integrate training programs and information dissemination, developing green skills in firms, and motivating consumers to consume green products.

Finally, like any other, our study is not free from *limitations*. First, although our study has an important and significant sample, perhaps later studies should expand the sample to different countries, testing the non-existence of bias in our results. On the other hand, although our study used the Community Innovation Survey as a questionnaire, subsequent studies should focus on other alternative measures to test the results and avoid possible measurement biases.

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Table 1
Eco-innovation factors

1. Internal factors	● Innovation capability ● Experience in eco-innovation
2. Institutional factors	● Public financial support
3. Market factors	● Eco-innovation new for the market ● Eco-innovation new for the firm

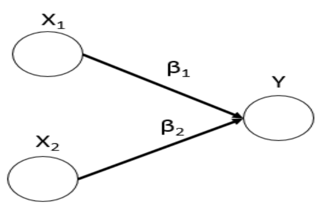
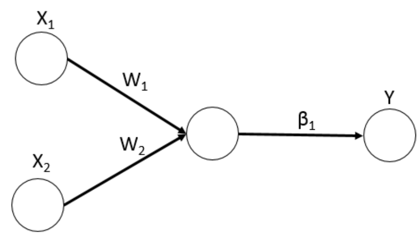
Direct Effect	**Interaction Effect**
	
$Y=\beta_0+\beta_1.X_1+\beta_2.X_2+e$	$Y=f(X1,X2)$ i) Interaction of variables X1 and X2: $Y=\beta_0+f(w_1.X_1+w_2.X_2)+e=\beta_0+\beta_1(w_1.X_1+w_2.X_2)+e$ Being, w_i, the weight of variable *i* in the interaction.

Figure 1. Direct and Interaction effect.

Table 2
Description of Database

1. PITEC is conducted bi-annually by Spain's National Statistics Institute (INE) since 2001.
2. PITEC questionnaire follows the Oslo Manual (OECD, 2005), replicating the Community Innovation Survey (CIS).
3. PITEC used the Central Directory of Spanish Companies (DIRCE), which includes Spanish companies located in the national territory.
4. PITEC contains firm-level data:
    a. Information about the company (size, sales, geographic market, type of economic activity, etc.)
    b. Information regarding its innovation activity (internal and external R&D expenditures, different types of innovation outputs, cooperation between firms, public financial support, and so on).

Table 3
Control Variables (t-1)

Control Variables (period 2010-11, t-1).
• Firm size *(Size)*: log of the number of employees. • Group variable (*Group*): it is whether the company has belonged to a companies' group. Values: 0 if it does not belong to a group and 1 if it does. • Manufacturing/Service variables (*Manufacturing/Service*): it is the company belongs to the manufacturing or service sector. Values: 1 for a manufacturing company and 0 for a service company

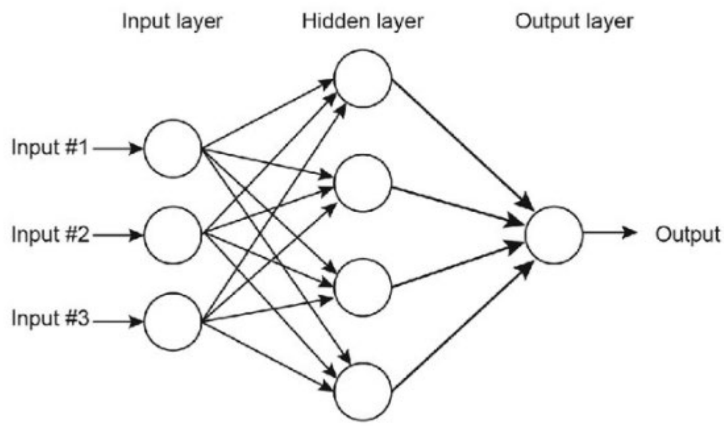


Figure 2. ANN Multilayer Perceptron (MLP) architecture

Table 4

Steps of the ANN procedure

1. Choice of the ANN typology	• We choose the ANN architecture with Multilayer Perceptron (MLP)
2. Design of architecture of ANN-MLP	• The network accuracy and the efficiency are dependent on various parameters: hidden nodes, activation functions, training algorithm parameters and characteristics such as normalization and generalization. • The number and size of hidden layers are 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.

3. Choice of the learning algorithm	• We are going to use is Backpropagation. This learning algorithm determines the connection weights of each neuron, readjusting the weights and minimizing the error.
4. Learning stage	• 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 minimizing the error. In the validation stage, the generalizability of the obtained architecture is checked. Lastly, the holdout data is used to validate the model.
4. Sensitive analysis	• A sensitive analysis is developed to quantify the influence of each input variable on the output variables.

Table 5
ANN-MLP architecture for interaction analysis

Output variable	ANN architecture	Activation Functions	Error
Energy eco-innovation (t)	6-5-1	• Hyperbolic tangent • Softmax	Cross-entropy
Environmental eco-innovation (t)	6-4-1	• Hyperbolic tangent • Softmax	Cross-entropy
Eco-innovation diversity (t)	6-4-1	• Hyperbolic tangent • Softmax	Cross-entropy

Table 6
Correlations among variables

	1	2	3	4	5	6
New market	1					
New firm	-.463**	1				
public financial support	.186**	-.048**	1			
innovation capability	.147**	.046**	.341**	1		
Energy experience	.087**	.043**	.135**	.269**	1	
Environmental experience	.132**	.004	.208**	.257**	.601**	1

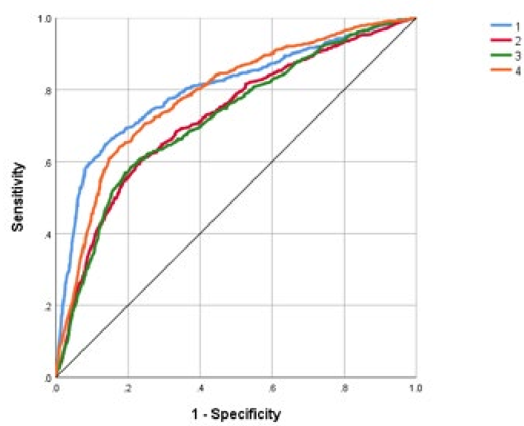
*p<0.05, **p<0.01

Table 7
Regression analysis

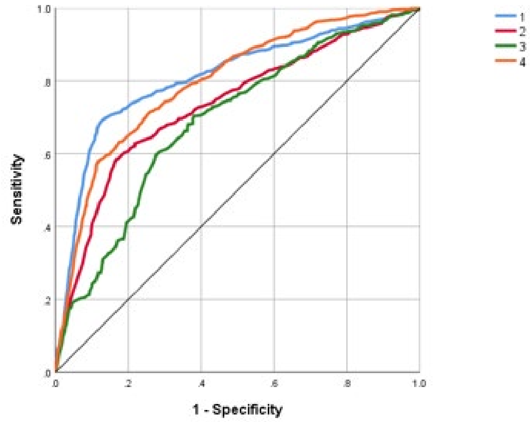
Variables (t-1)	**Energy eco-innovation (t)**	**Environmental eco-innovation (t)**	**Eco-innovation (t)**	**VIF**
	Model 1	**Model 2**	**Model 3**	
Public financial support	.095*	.131**	.117**	1.055
Innovation capability	.147***	.072*	.125***	1.129
New market	.019	.125	.040	1.335
New firm	.170	.105	.134	1.274
Energy experience	1.119***	.185***	.757***	1.587
Environmental experience	.147***	1.085***	.701***	1.581
Group	.318***	.156*	.170**	1.049
Size	.023	.045*	.010*	1.034
Manufacturing/Service	.117**	.199**	.138**	1.099
-2 Log Likelihood	6440.596	7322.020	10604.528	
Chi-Square	1324.271	1428.658	1620.045	
Sig.	.000	.000	.000	
Cox and Snell	.336	.357	.394	
Nagelkerke	.359	.382	.403	
McFadden	.149	.162	.132	

*p<0.05, **p<0.01, *** p<0.001

ANN 1: Dependent Variable: *Energy Eco-innovation*



ANN 2: Dependent Variable: *Environmental Eco-innovation*



ANN 3: Dependent Variable: *Environmental Eco-innovation*

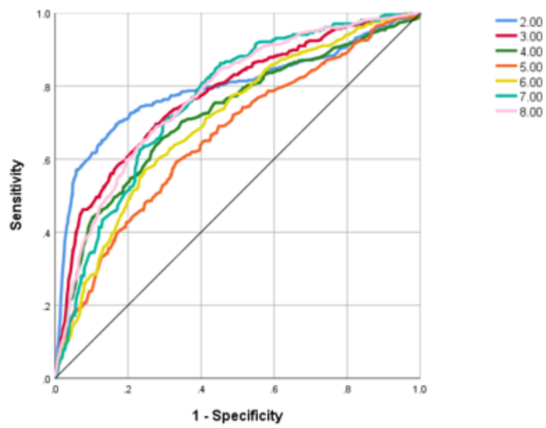


Figure 3. ROC curve (Receiver Operating Characteristics)

Table 8
ANN-MLP simulation for each of the dependent variables

Variable (t-1)	**Energy eco-innovation (t)**		**Environmental eco-innovation (t)**		**Eco-innovation diversity (t)**	
	Importance	Normalized Importance	Importance	Normalized Importance	Importance	Normalized Importance
Energy experience	.118	24.7%	.476	100.0%	.438	100.0%
Environmental experience	.499	100.0%	.113	24.3%	.427	97.6%
Public financial support	.125	25.0%	.140	29.4%	.049	11.1%
Innovation capability	.184	36.8%	.110	23.0%	.040	9.1%
New market	.106	21.3%	.086	18.1%	.022	5.1%
New firm	.086	17.3%	.071	14.8%	.024	5.4%