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Forecasting the macrolevel determinants of entrepreneurial opportunities using artificial intelligence models

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ABSTRACT

To date, entrepreneurship researchers have tended to avoid state-of-the-art artificial intelligence techniques; in this paper, we fill that gap. Based on eclectic entrepreneurship theory, we present an original work that uses artificial intelligence to forecast the macrolevel determinants of entrepreneurial opportunity. Modern artificial intelligence could open new areas for future research opportunities in entrepreneurship and help close the gap between theory and practice. Our empirical analysis offers two major results by using a panel dataset of 149 countries covering 2007–2018 and six machine-learning models. First, entrepreneurs prefer to exploit opportunities in countries with stable economic governance that provide high education standards, health, social capital, and a safe, natural environment. Second, CatBoost regression performs better in predicting entrepreneurial opportunity compared to linear regression and more advanced machine-learning models. Recommendations for policy-makers and managers and directions for future studies are also discussed.

1. Introduction

Organizational success stories in international markets constitute a major topic in the entrepreneurial field (McDougall et al., 1994). The success of a new business project is largely dependent on some preliminary decisions, most importantly selecting a location for the new opportunity. When entrepreneurs possess more background knowledge about the location, risks, and perspectives of certain opportunities, they are more likely to exploit these opportunities. They use available information to evaluate the appeal of a country to pursue these existing opportunities. Increasing data availability allows entrepreneurs to collect more information and thus to make better entrepreneurial decisions. Big data is being adopted by companies more frequently, particularly in companies seeking new methods to build smarter capabilities to face the challenges of dynamic processes. Consequently, big data can be used more efficiently for opportunity selection across countries thanks to recent enhancements in artificial intelligence (AI), machine learning, and time series forecasting models (Lecun et al., 2015; Loureiro et al., 2018; Kraus et al., 2019).

The impetus for this research is the large number of published studies that focus on the macrolevel determinants of entrepreneurship. Prior studies demonstrate that factors such as economic environment, governance, health and education levels are important determinants of entrepreneurial activity (Carbonara et al., 2016; Hall et al., 2016; Hoogendoorn et al., 2016; Menezes and Canever, 2017; Nikolaev et al., 2018). However, these research works only focus on individual or specific groups of variables, such as resource and ability indicators, institutional indicators, economic indicators, or cultural indicators (Klapper et al., 2007), and do not include all of them together. To our knowledge, no empirically estimated entrepreneurship model considers the joint impacts of these indicators on entrepreneurial opportunities. These studies also deliver divergent results regarding the importance and impact of each of these indicators. When looking closely, we see that most of these researchers use the Global Entrepreneurship Monitor (GEM). In this study, we apply machine-learning models to the Legatum Institute database. Finally, as Wennberg and Anderson (2019) pointed out, entrepreneurship researchers must invoke new alternative approaches to explore complex data and expand the limitations of traditional models. Our study uses a novel gradient-boosting method, namely, the CatBoost regression method suggested by Prokhorenkova

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et al. (2018).

This article adds to the ongoing literature in different ways to fill the previously mentioned gaps. We contribute to the eclectic theory of entrepreneurship (ETE) by identifying and predicting the factors (supply-side, demand-side and governance quality) influencing entrepreneurial opportunity. Concerning supply-side factors, we find that good standards of education, health and social capital are key determinants to predict entrepreneurial opportunity. This result supports the population theories that claim that people are the key actors in social and economic changes. It also supports the arguments of studies employing endogenous growth theory, in which investment in human and social capital produces spillover effects, which, in turn, increase new venture creation.

Regarding the demand-side factors of ETE, this study extends the existing studies on opportunity entrepreneurship by examining the roles of economic quality and the natural environment in predicting entrepreneurial opportunities. Our findings with regard to government intervention — governance quality — support the institutional theory of entrepreneurship that a country's governance system is a key factor in determining the national level of entrepreneurship. In addition, this study proposes a new notion of entrepreneurial opportunity, a form of multidimensional opportunity, measured by the sum of existing opportunities in a country: access to infrastructures such as the internet and transport and credit; the flexibility of business such as the costs of starting a business and of hiring and firing; and clear and fair regulation such as intellectual property rights and perceptions of meritocracy and opportunity. Our notion of entrepreneurial opportunity is based on research on how entrepreneurship stimulates innovation and generates economic growth and the positive effects that result from individuals' realization of their entrepreneurial potential. In this framework, entrepreneurial opportunity is more linked to certain aspects of prosperity, such as education, the quality of the economy, governance, health, the natural environment, and the safety and security of countries.

From a methodological viewpoint, we applied an AI approach, particularly machine- and deep-learning models, to forecast the macrolevel determinants of entrepreneurial opportunity. Using AI in entrepreneurship research could help promote the development of entrepreneurship theory and bridge the gap between theory and practice (Lévesque et al., 2020). A significant number of studies have been conducted on the use of AI by entrepreneurs in their businesses, for example (Chalmers et al., 2021; Agrawal et al., 2018; Cockburn et al., 2018; Davenport et al., 2020; Townsend and Hunt, 2019), yet entrepreneurship researchers have not used AI in their studies (Lévesque et al., 2020). In addition, big data studies constitute a new methodological frontier in entrepreneurship research, and big data represent an opportunity to make substantial contributions to entrepreneurship research (Schwab and Zhang, 2019). Finally, Maula and Stam (2020) highlight the common empirical concerns in quantitative entrepreneurship research and discuss new opportunities for enhancing rigor, including applying new techniques such as AI, machine learning and text mining. This study is a step toward closing this gap. In this article, we have chosen to apply AI techniques for several reasons. The first reason is the nature of our data; many variables of interest do not follow a normal probability distribution function but instead follow very skewed power distributions (Crawford et al., 2015), which require the use of AI and machine-learning methods. The second reason is that we have a relatively large dataset (the Legatum Institute). We used AI techniques to analyze this dataset and then visualize the analyses (Fig. 2, Fig. 3, Fig. 5, Fig. 6). In this study, we employed several AI forecasting techniques ranging from traditional linear regressions to more complex models (support vector regression, neural networks, random forest, deep neural networks, CatBoost regression). The third reason is that the AI model performs better than traditional statistical methods for processing and analyzing data. We compared forecast performance among the six machine-learning models using five evaluation metrics (RMSE, MSE, MAE, MAPE, and R2). We found that all AI prediction algorithms perform better than the traditional linear regression algorithm. Moreover, CatBoost models are shown to be the best algorithm for forecasting entrepreneurial opportunities, with the highest performance (R2 $\geq$ 92.7%) and the fewest errors (RMSE 2.930, MAPE 0.048).

To our knowledge, no previous studies have forecasted time series data using entrepreneurial opportunity as a dependent variable. The rest of the article is divided into five sections. After the introduction, Section 2 describes the theoretical background and related literature on the determinants of entrepreneurial opportunity. Section 3 discusses the methodology and the data used in the analysis. Section 4 summarizes the results of the machine- and deep-learning models. Section 5 discusses the results, and Section 6 concludes.

2. Theoretical background and related literature

2.1. Concept of opportunity entrepreneurship

The existing entrepreneurship literature provides several definitions of entrepreneurship, and researchers do not agree on a single definition (Wiklund et al., 2011). This difference depends on the subject of the research enterprise Gedeon (2010). In the macroeconomic analysis of entrepreneurship, the previous literature presents different studies that adopt different points of view on the roles of entrepreneurs in economic activity. First, entrepreneurs are considered the principal production factors of economic activity and are seen to act by evaluating and exploiting the best opportunities in the market (Hébert and Link, 1988). They are business managers whose benefits are not the rewards for taking risks but rather salaries for a rare sort of work. From this perspective, the rate of self-employment is used to differentiate entrepreneurial activity between nations (Acs et al., 1994; Parker, 2004). Another point of view is that entrepreneurs are considered arbitrageurs who balance the demand and supply of goods and services (Knight, 1921). According to Kirzner (1973), entrepreneurs are seen as riskholders who react to market opportunities in an ever-changing world, and thus strive to balance economic activity. Researchers who adopt this view apply business property rate as a measure of entrepreneurship (Stephan and Uhlanr, 2010). In a third viewpoint, entrepreneurs are the innovative agents who drive production levels and identify novel opportunities (Schumpeter, 1934). Different measures are used in line with this view. Some scholars use firm entry rates (e.g., Acs and Audretsch, 1989; Austin and Rosenbaum, 1990), others use survival rates (e.g., Bartelsman et al., 2004; Delgado et al., 2010), while others use self-employment exit and entry rates (e.g., (Hamdan, 2019; Lin et al., 2013). Entrepreneurship researchers have also adopted the view suggested by Shane and Venkataraman (2000), who state, "*entrepreneurship involves the nexus of two phenomena: the presence of lucrative opportunities and the presence of enterprising individuals*". In this spirit, entrepreneurs are seen as people attracted by the interplay between the supply and demand of entrepreneurial activity (Thai and Turkina, 2014), while entrepreneurship is defined as the involvement of individuals in starting a business. In this connection, the macro data offered by the Legatum Institute, the World Development Indicators, and the Global Entrepreneurship Monitor are increasingly popular in the current entrepreneurship literature .

Among these different views, the last viewpoint is the most relevant to our study because it aims to identify the determinants of entrepreneurial activity. Thus, we examined the key studies to identify the most commonly acknowledged measures and definitions of opportunity entrepreneurship.

Entrepreneurship researchers have looked at entrepreneurial opportunities in different ways. For some scholars, the entrepreneurial opportunity is a novel subject (Ardichvili et al., 2003; DeTienne and Chandler, 2007). For other scholars, it is the demand for introducing a product (e.g., Eckhardt and Ciuchta, 2006). The procedures used by entrepreneurs to create, identify, locate, or exploit opportunities have also been studied (e.g., Ensley et al., 2000; Kolvereid and Isaksen, 2006; McMullen et al., 2007; Vlados and Chatzinikolaou, 2020). Hansen et al.

(2011) analyzed definitions of entrepreneurial opportunity and opportunity-related processes (over 19 years). They found that the literature on the entrepreneurial opportunity and opportunity-related processes is highly fragmented, particularly in terms of operational definition. However, their examination of conceptual definitions implies that there is not as much fragmentation as might appear. To reduce the fragmentation, they create six composite definitions from the conceptual definitions. In our study, we adopt the following composite definition: "an opportunity is an entrepreneur's perception of a feasible means to obtain/achieve benefits" (Brunetto and Farr-Wharton, 2007; Casson and Wadeson, 2007; Dimov, 2002, 2007; Gnyawali and Fogel, 1994).

2.2. Eclectic theory of entrepreneurship

Since entrepreneurship concerns people's engagement in the creation of new ventures, Verheul et al. (2001) suggest the eclectic theory of entrepreneurship (ETE), which includes a large set of micro and macro factors that influence the rate of entrepreneurs at the country level (Fig. 1). According to this theory, this rate can be influenced by the following six basic elements: demand-side factors, supply-side factors, individual decision-making, actual and equilibrium rates, government intervention, and culture.

For the demand-side factors, entrepreneurial opportunities are influenced by a set of factors, particularly the level of development, globalization, and technologies, which affect the market demand for goods and services and the industrial structure, leading to more entrepreneurial opportunities. Regarding supply-side factors, entrepreneurial opportunities are influenced by population characteristics, the participation of women, and the level and disparity of revenue. With the required resources, abilities, and preferences, these supply-side factors generate potential entrepreneurs who can exploit the existing entrepreneurial opportunities.

Hence, the decisions made by entrepreneurs, i.e., an individual's occupational choices, considers the availability of entrepreneurial opportunities and individual characteristics. When making entrepreneurial decisions, individuals are assumed to compare the risks of alternative types of occupational employment versus the risk-reward profile of self-employment, i.e., wage jobs or unemployment versus self-employment. These decisions materialize as the exit and entry rates of entrepreneurs at the aggregate level (Verheul et al., 2001).

Both dynamic and static entrepreneurial decisions determine a country's actual rate of entrepreneurial activity (see E in Fig. 1), which can diverge from the "equilibrium" level of entrepreneurship (see E* in Fig. 1). This "disequilibrium" (see E-E*in Fig. 1) could be re-established either by market forces, i.e., a lack or surplus opportunity entrepreneurship, leading, respectively, to exit and entry of entrepreneurs, or by government intervention in the economic process, which may affect the key determinants of entrepreneurial decisions. For instance, improving governance quality may increase opportunities to start a business thanks to better regulation of the business environment, well-defined property ownership, effective regulation of the economy, and reduction of bureaucratic obstacles (see arrow G1 in Fig. 1). Government policies may determine the supply of entrepreneurs and their decisions (see arrow G2 in Fig. 1). The knowledge and skills of entrepreneurs can be determined by education, facilitating the accessibility of capital and provision of information through consulting or counseling (see arrow G3 in Fig. 1). Changes in an individual's preferences are more difficult to influence but may be done by the media and the education system (see arrow G4 in Fig. 1). Furthermore, labor-market regulations, tax incentives, and bankruptcy legislation jointly determine different employment opportunities' net profits and risks (see arrow G5 in Fig. 1).

In summary, the ETE offers a theoretical framework for understanding the micro- and macrolevel determinants of entrepreneurship at the country level. However, to our knowledge, no prior studies have used this theoretical framework to predict and identify the determinants of opportunity entrepreneurship.

2.3. Determinants of opportunity entrepreneurship

In accordance with the above discussion, ETE highlights a set of factors influencing the rates of entrepreneurship at the macro level, including demand-side factors (economic opportunities), supply-side factors (resources and abilities), governance quality, and culture. In this study, we did not include cultural factors due to the inaccessibility of data for some countries.

2.3.1. Economic opportunities

Individuals living in economies with a difficult economic environment and facing socioeconomic marginalization are subject to internal discontent that obliges them to start a business in a self-employed form (Baker et al., 2005; Serviere, 2010). In this context, Thai and Turkina (2014) argue that as an economy grows, it offers opportunities that may make self-employment a less attractive occupation choice. Therefore, economic quality is a factor that affects the growth in opportunity entrepreneurship by increasing the demand for goods and services. This argument is in line with Jackson's study (1984), which argues that levels of wealth and income determine the diversity of consumer demand. Strong demand encourages the production of new goods and services. The economic development stage influences entrepreneurs' supplies by making financial resources more accessible for business creation (Stoica et al., 2020). In addition, recent research and debate on entrepreneurship have shown an increased interest in the role of the environment as a stimulus for creating new organizations. Living environments are of great importance to promote health and quality living conditions

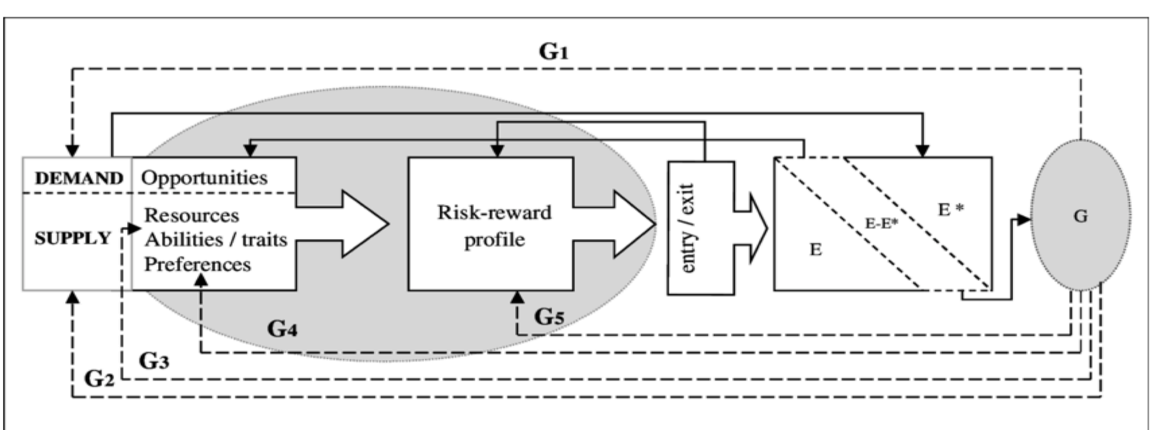

Fig. 1. The framework of determinants of entrepreneurship. (Source: Verheul et al. (2001), p. 10).

(Dhahri et al., 2021). A sound natural environment leads to better quality of life (Kumari et al., 2021), while the stress created by negative living conditions has a greater influence toward the creation of new firms (Cooper, 1973). Shapero (1972) concludes that living conditions are by far the most crucial determinant of location decisions. For example, the accessibility of a natural environment and attractive views of nature within an individual's living environment are significant contributors to creating entrepreneurial opportunities (Cohen and Winn, 2007). Infrastructure and policy solutions should ensure a sound and durable natural environment to boost long-term investments and national wealth. These arguments allow us to formulate the following hypothesis:

Hypothesis 1: Economic opportunities increase entrepreneurial opportunity.

2.3.2. Resources and abilities

People's resources and abilities are at the core of entrepreneurial activity (Kor et al., 2007). It has been shown that the human capital acquired by education is one of the main determinants of entrepreneurial success and performance (Millán et al., 2014; Omri et al., 2015; Omri and Afi, 2020). The education system plays an important role in encouraging commercial awareness, improving the social status of entrepreneurs, and promoting entrepreneurial skills (Gavron, 1998; Matlay, 2005; Omri, 2020). Education plays a key role in creating entrepreneurial opportunities, while new businesses profit from the presence of educated consumers and an informed labor force (Millán et al., 2014). Additionally, several studies on entrepreneurship have addressed the subject of health (Kets de Vries, 1980). Health status is positively associated with entrepreneurial opportunity (Rietveld et al., 2016). Health is taken into account when calculating the expected utility of entrepreneurship. Therefore, individuals in a poor state of health will not search for entrepreneurial opportunities because they will consider the decreased expected utility and outcomes. Thus, this positive link between entrepreneurial perceptions and health explains health-related entrepreneurship selection (Hatak and Zhou, 2021). Furthermore, social capital ensures that entrepreneurs have the moral backing that they require. On the other hand, it presents them, with models designed to improve their startup opportunities and, on the other hand, allows them to stand up to the obstacles that emerge at the point when the firm is consolidated (Adler and Kwon, 2002). Regarding this discussion, we formulate the following hypothesis:

Hypothesis 2: Increased resources and abilities increase entrepreneurial opportunity.

2.3.3. Governance quality

The World Governance Indicators define governance quality as "the traditions and institutions by which authority in a country is exercised. This includes the process by which governments are selected, monitored and replaced; the capacity of the government to effectively formulate and implement sound policies; and the respect of citizens and the state for the institutions that govern economic and social interactions among them." It occupies an important place in the current literature on entrepreneurship. In recent years, solving the enigma of the link between entrepreneurship and governance has been an active area for policy research and discussion. For example, previous studies, such as Kaufmann et al. (2006) and Omri (2020), show that strict laws, transparent registration procedures, and sound political and economic institutions positively impact entrepreneurial activity. Comparative studies confirm these conclusions at the country level (Aidis et al., 2008). Poor governance systems negatively impact the level of entrepreneurship due to the influence of institutional ineffectiveness (Douhan and Henrekson, 2010; Ali et al., 2020).

Additionally, in the event of violence and insecurity, entrepreneurs must invest extensively to protect their business and cover the extraordinary costs resulting from these circumstances. Several studies present violence as an obstacle to entrepreneurship since costs related specifically to violence lead to a significant decline in the financial performance of businesses in a country. An assessment of insecurity as an additional determinant of entrepreneurship is therefore obviously fundamental. However, very few researchers have examined the effect of insecurity and violent conflict on entrepreneurship (Brück et al., 2013). Regarding these arguments, we formulate the following hypothesis:

Hypothesis 3: Good governance increases entrepreneurial opportunity.

3. Data and methodology

3.1. Data and variables

We obtain time series data for 149 countries from the Legatum Institute database (https://www.prosperity.com/about/resources) over 2007–2018. The data include economic quality, which assesses a country's success in socioeconomic policies, economic satisfaction, economic aspirations, wealth transfer, participation, and product quality. *Education* measures countries' performance concerning access to education and human capital. Governance assesses a country's success in terms of efficient and responsible administration, free and equal elections, democratic engagement, the rule of law, and equality. *Safety and security* measures countries' performance in national security, personal precariousness, and personal safety. *Social capital* assesses social stability and commitment, and cultural and family networks, educational outcomes, and intellectual capital. *The natural environment* measures countries' geography, nature and air quality. *Health* measures performance in basic health outcomes, health infrastructure, preventative care, and physical and mental health. The seven factors of entrepreneurial opportunity predictors indicate an entrepreneurial climate in which citizens can pursue new ideas and opportunities. A more detailed definition of our variables is presented in Table 1. Table 2 summarizes the descriptive statistics of the full sample, and Fig. 2 displays a picture of the correlations between the variables used in this study.

3.2. Machine- and deep-learning models

3.2.1. Linear regressions (LR)

Multiple regression analysis is widely used by researchers in the behavioral sciences, the health sciences, education, and business

Table 1
Definitions of variables.

Variables	Definition
Entrepreneurial opportunity	The entrepreneurial environment in which people can pursue opportunities for better lives, more wealth and greater social wellbeing.
Economic opportunities: *Economic quality*	Countries' performance in five fields: structural strategies; economic forecasts, and happiness; richness delivery; participation; and output efficiency and variety.
Natural Environment	Countries' performance in four areas: land and marine areas devoted to nature, pesticide usage and air quality.
Resources and abilities:	
Education	Countries' performance in four fields: education accessibility, quality of education, and human capital.
Health	Countries' performance in three fields: basic patient effects, health infrastructure and preventive treatment, and physical and emotional health.
Social Capital	Countries' performance in three areas: social solidarity and commitment, group and family networks, standards of education and intellectual resources.
Governance quality: *Governance*	Countries' performance in four fields: efficient and accountable government, fair elections and political involvement, the rule of law, and the level of a country's democracy.
Safety and Security	Countries' performance in three areas: political security, personal precariousness, and stability.

Source: Legatum Institute (2019).

Table 2
Descriptive Statistics.

	Entrepreneurial opportunity	Economic Quality	Governance	Education	Health	Natural environment	Safety and security	Social capital
Mean	50.574	61.164	49.960	61.979	69.540	59.790	74.831	49.993
Median	49.606	60.489	47.283	64.663	71.676	59.989	74.323	49.504
Maximum	78.606	82.967	86.679	87.462	86.103	84.478	95.695	69.090
Minimum	26.014	35.754	19.182	18.710	39.509	34.495	36.408	27.284
Std. Dev.	10.841	9.626	15.261	15.101	10.002	9.880	11.081	7.445
Skewness	0.356	0.221	0.549	−0.589	−0.566	−0.073	−0.396	0.337
Kurtosis	2.624	2.293	2.539	2.614	2.351	2.521	2.999	2.755
Observations	1788	1788	1788	1788	1788	1788	1788	1788

Fig. 2. Pearson correlation matrix between variables.

(Cohen and Winn, 2007). The linear regression technique aims to specify the relationships between a set of explanatory variables Xj and a set of dependent variables Y. The ordinary least squares (OLS) method is used to estimate the relationship between variables and the outcome and can be expressed as follows:

$$Y_i = \alpha_0 + \alpha_1 X_1 + \ldots + \alpha_n X_n + \varepsilon_i$$

where the parameters $\sigma_1 \ldots, \sigma_n$ represent the estimate coefficients of X_1, …, X_n, respectively, and ε_i represents the random error, which denotes the difference between the observed and actual values of the outcome.

Linear regression suffers from many statistical limitations, such as in regards to correlation, endogeneity, complex data, noisy data and nonlinear relationships; several authors call for the employment of alternative approaches to overcome the drawbacks of multiple regression analysis (Woodside, 2013; Ben Jabeur, 2020).

3.2.2. *Support vector regression*

Support vector regression (SVR) was initially proposed by Cortes and Vapnik (1995). SVR was initially employed in classification problems and then extended to regression problems. It is structured to match established data to output parameters before forecasting uncertain data using trained models. Considering a set of historical data {(X_i, Y_i) $i = 1$, ⋯, N}, SVR formulates an optimized hyperplane function that denotes the nonlinear relationship between input variables and the output. This SVR function could be expressed as follows:

$$f(X) = W^T \psi(X) + c$$

where f(x) denotes the function for forecasting values, where X denotes the input features, W is the weight of the coefficient connected to each input vector X_i, and C is the bias term. The achievement of the SVR depends on the selection of a kernel function, which can help decrease the computing time of the regression (Dhiman et al., 2019).

3.2.3. *Neural networks*

The neural network (NN) model is widely used to approximate highly complex phenomena with high performance. Not only is it a powerful tool in classification modeling. It also performs well when examining relationships. As pointed out by Sulandari et al. (2019), one of the great advantages of the NN technique is that it does not need specific assumptions to run a model. A single network architecture is designed featuring an input layer, a hidden layer, and an output layer. The neurons obtain input values from interconnections and produce outputs using an activation function. Following Chang et al. (2009), the network model can be specified as:

$$Y_i = f(X_j) = f\left(w_{0j} + \sum_{i=1}^{N} w_{ij} x_i\right)$$

where w_{ij} are the setting threshold values for bias weights, f is the activation function, and Xj and Y_j are the input and output variables, respectively. Many types of neural network algorithms have been created in recent years, especially deep-learning techniques.

3.2.4. Random forest

Random forest regression (RF) is a machine-learning technique devised by Breiman (2001) in 2001. RF uses bootstrap sampling to extract several samples from the original data. The basic idea of RF is to combine multiple weak decision trees into one strong decision tree to improve the performance regression of the individual trees. The framework is executed by averaging the outputs of all trees. Consequently, as pointed out by Li et al. (2018), the estimation Y of the output can be calculated as follows:

$$\mathrm{Y_i} = \frac{1}{q}\sum_{i=1}^{q}\widehat{h}\left(X, S_n^{\theta_i}\right)$$

where Y_i denotes the output for each tree, q represents the number of trees, X is an input vector of variables, $\widehat{h}$is the prediction function, and S_n denotes the training set containing n observations. A subset is produced with replacements from the original sample to run every regression tree construction. At each setup, when a regression tree is created with the training sample, the out-of-bag sample is employed to assess the performance of the regression tree.

3.2.5. Deep neural networks

Deep neural networks (DNNs) have been successfully implemented in a variety of fields, such as energy (Liu et al., 2019), finance (Krauss et al., 2017; Jabeur et al., 2019; Maqsood et al., 2020) and tourism (Law et al., 2019; Zhang et al., 2019). DNNs can easily handle models with highly complex and nonlinear relationships between predictors and outcome variables. In various situations, deep neural networks outperform the best traditional machine learning techniques. A feedforward neural network architecture is implemented, and stochastic gradient descent is used as a training algorithm to run the model. As pointed out by Kraus et al. (2019), deep neural networks can be formalized by combining many single-layer networks into a k-layer deep neural network:

$$\mathrm{f(X)}_{DNN} = \frac{f_{1NN}(f_{1NN}(\ldots f_{1NN}(X)))}{k}$$

where f_{1NN} is a single-layer perceptron computed using an activation function including the sigmoid function, hyperbolic tangent, or rectified linear unit (ReLU). According to Lecun et al. (2015), the rectified linear unit is commonly used for deep neural networks. Our study implemented deep neural networks via H2O (2019), an open-source machine-learning platform, and then executed them via R software (R Core Team, 2017).

3.2.6. CatBoost regression

Ensemble frameworks have been successfully used for a variety of regression problems Dev and Eden (2019). CatBoost is a new gradient boosting decision tree algorithm proposed by Prokhorenkova et al. (2018) to handle categorical features more efficiently. CatBoost uses a new efficient schema to estimate leaf values during the selection of tree architectures, which minimizes overfitting. Additionally, CatBoost introduces an innovative algorithm to address the overcoming of existing implementations of gradient boosting algorithms. The gradient descent function (Prokhorenkova et al., 2018) is described as follows:

$$h^t = \mathrm{arg}min\frac{1}{N}\sum^{\left(-g^t(X_k,Y_k)-h(X_k)\right)^2}$$

where X_k is the random vector of m features, Y_k is the target, and g is a least-squares approximation by the Newton method. The CatBoost model uses random permutations of the training data to run the model and calculates an average label value for the example with the same class value. In addition, to increase performance, CatBoost employs oblivious decision trees, which are less prone to overfitting and can meaningfully improve performance speed during tests.

4. Results

4.1. Results of linear regressions

The multiple estimation method used in this study is ordinary least squares, although it suffers from numerous problems such as heteroscedasticity and autocorrelation. To deepen our analysis, we also used fully modified ordinary least squares (FMOLS) and dynamic ordinary least squares (DOLS), which both outperform OLS regression and address the potential endogeneity of regressors (Kao and Chiang, 1999; Pedroni, 2000).

The results of the multiple regression analysis are presented in Table 3. Regarding the economic opportunity variables, we found that *economic quality* has a positive and statistically significant effect on entrepreneurial opportunity ($\beta = 0.213, p < 0.001$ (OLS), $\beta = 0.249, p < 0.05$ (FMOLS) and $\beta = 0.280, p < 0.001$ (DOLS)). This conclusion supports the findings of Dhahri and Omri (2018), who claimed that increased economic activity opens up new business opportunities. Moreover, the *natural environment* variable is statistically significant ($\beta = 0.211$, $p < 0.001$). We can explain this result by considering two factors. First, the presence of natural environmental areas (national parks, aquatic parks, forests and beaches) contributes greatly to local, regional, state and national economies by enhancing the tourism sector (Wood et al., 2006). For example, 23% of international tourists surveyed in Australia said that their decision was based on the chance to experience natural landscapes and wildlife Chua (2001). Entrepreneurship opportunity is linked to the tourism sector through local knowledge and local culture and to simple business plans and low environmental impacts and costs (Séraphin et al., 2013). These two elements create good prospects for increasing entrepreneurial opportunities in an emergent country. Tourism represents a source of entrepreneurship opportunities that can help to boost regional growth (Dana et al., 2014).

For the resource and ability variables, as expected, we found that *education* has the highest contribution toward entrepreneurial opportunity ($\beta = 0.203, p < 0.001$ (OLS), $\beta = 0.935, p < 0.05$ (FMOLS) and $\beta = 0.713, p < 0.001$ (DOLS)), meaning that the higher the education level in a country, the greater the number of opportunities identified and exploited by entrepreneurs (Anho, 2011; Omri and Afi, 2020). Better *health* ($\beta = 0.289$, $p < 0.001$ (FMOLS)) maximizes the utility of entrepreneurship, which in turn is taken into consideration in the entrepreneurial decision to pursue an opportunity (Rietveld et al., 2016 ;Van der Zwan et al., 2016). The *social capital* variable is a significant predictor of opportunity ($\beta = 0.112$, $p < 0.05$ (FMOLS)). This confirms the conclusion of Bhagavatula et al. (2010), who reported a positive effect of social capital on the entrepreneurial opportunity.

Furthermore, *governance* exhibits a positive impact on the entrepreneurial opportunity in all estimated models. This finding is in line with (Thai and Turkina, 2014) conclusions. They documented that the quality of governance encourages formal entrepreneurship, contrary to Friedman's (2011) findings. However, unexpectedly, *safety and* security have negative effects on the dependent variable. Nevertheless, we argue that in emerging countries, the entrepreneurial opportunity is greater than in developed countries. Emerging countries offer considerable opportunity for entrepreneurial activity. In contrast, the business market in developed countries tends to be saturated, decreasing the motivation for nascent businesses and, subsequently, for entrepreneurship in general.

4.2. Results of machine-learning models

4.2.1. Feature importance by Catboost model

In general, previous studies using machine-learning models in management fail to consider the interpretability of the outputs. However, boosted trees try to resolve this difficulty and can be relatively well interpreted compared to neural networks. This section outlines model interpretation, variable importance measures, and partial dependence plots.

Table 3
Results from multivariate regression analysis.

	OLS Coefficient	*P* value	Panel FMOLS Coefficient	*P* value	Panel DOLS Coefficient	*P* value
Intercept	4.557***	(0.000)				
Economic Quality	0.213***	(0.000)	0.249***	(0.000)	0.280***	(0.000)
Governance	0.318***	(0.000)	0.161***	(0.000)	0.1236***	(0.000)
Education	0.203***	(0.000)	0.935***	(0.000)	0.713***	(0.000)
Health	0.068**	(0.011)	0.289***	(0.000)	0.245***	(0.000)
Safety and Security	−0.067***	(0.000)	−0.154***	(0.000)	−0.126***	(0.000)
Social Capital	0.156***	(0.000)	0.112***	(0.005)	0.081***	(0.001)
Natural Environment	−0.052	(0.004)	0.211***	(0.000)	0.120***	(0.002)
R-squared	0.787		0.951		0.948	

Notes: p values are in parentheses. ***, **, and * indicate significance at the 1%, 5% and 10% levels, respectively.

Friedman (2001) proposed using *feature importance* to quantify the importance of single variables in predicting Y for gradient boosting trees. Fig. 3 shows the feature importance of each independent variable. *Education,* followed by governance, has the highest feature importance, meaning that a country's education and governance systems are the most important factors to predict entrepreneurial opportunity. These factors are followed by *health* and *economic quality*.

After identifying the relative importance of each input feature, the partial dependence plots in Fig. 4 provide an effective way to understand the relationship between predictors and the outcome. Partial dependence plots are employed to visualize the general impact trends of the four most important variables in entrepreneurial opportunity, as in Friedman (2001). We can observe a positive relationship between the variables and the outcome. The findings confirm previous results with multiple linear regressions and indicate that education, governance, health and economic quality positively impact entrepreneurial opportunity. To further our analysis, we also show the centered individual conditional expectation (c-ICE) plots proposed by Goldstein et al. (2015) in Fig. 5). The c-ICE plots improve the partial dependence plot by graphing the functional correlation between the entrepreneurial opportunity and the feature for individual observations. Fig. 5 shows the c-ICE for the four most important variables. The results provided by the partial dependence plots and centered individual conditional expectations are in accordance with those of Thai and Turkina (2014) and Ben Youssef et al., (2018), who documented a positive relationship between economic growth, governance and entrepreneurial opportunity.

Fig. 6 presents two-variable partial dependence plots, which are useful for showing the interaction effect between two variables on forecasting entrepreneurial opportunity. For example, it can show the existence of positive interaction between education and governance since increasing both features leads to increased entrepreneurial opportunity. The highest positive relationship was between the 60 values for education input and the 50 values for governance input. In Fig. 7, we display two additional examples of two-dimensional partial dependence plots explaining second-order effects.

4.2.2. Comparison of model performance

We divided the data into a set of 80% to train the model and a set of 20% to predict model performance. Five popular evaluation metrics are used to assess and compare the forecasting performance among the six machine learning models: the root mean square error (RMSE), mean square error (MSE), mean absolute error (MAE), mean absolute percentage error (MAPE), and the coefficient of determination (R^2). The specific definition of each of these metrics can be calculated as follows:

$$RMSE = \sqrt{\frac{1}{N}\sum_{h=1}^{N}\left(\widehat{Y}_h - Y_h\right)^2}$$

$$MSE = \frac{1}{N}\sum_{h=1}^{N}\left(\widehat{Y}_h - Y_h\right)^2$$

$$MAE = \frac{1}{N}\sum_{h=1}^{N}\left|\widehat{Y}_h - Y_h\right|$$

$$\mathrm{MAPE} = \frac{1}{N}\sum_{h=1}^{N}\left|\frac{\widehat{Y}_h - Y_h}{Y_h}\right| * 100$$

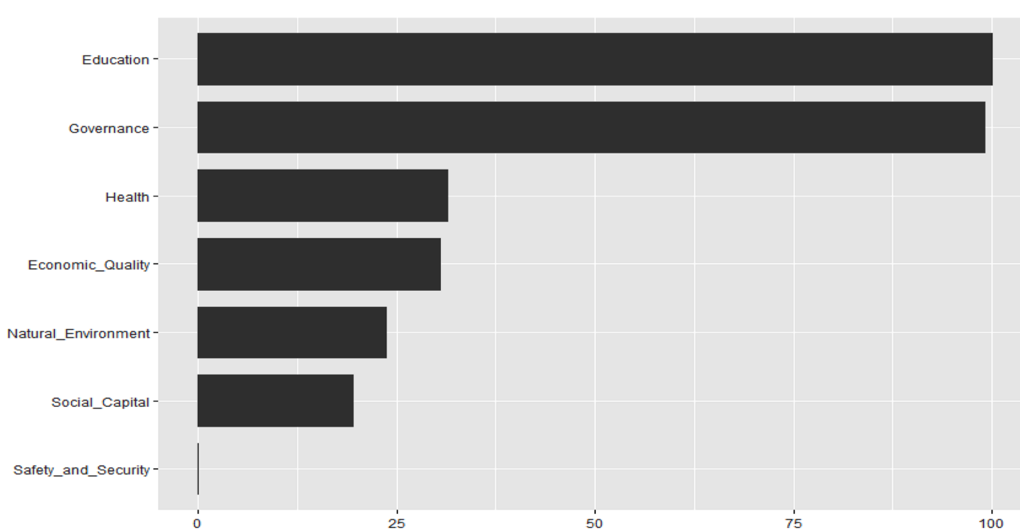

Fig. 3. Feature importance using CatBoost model.

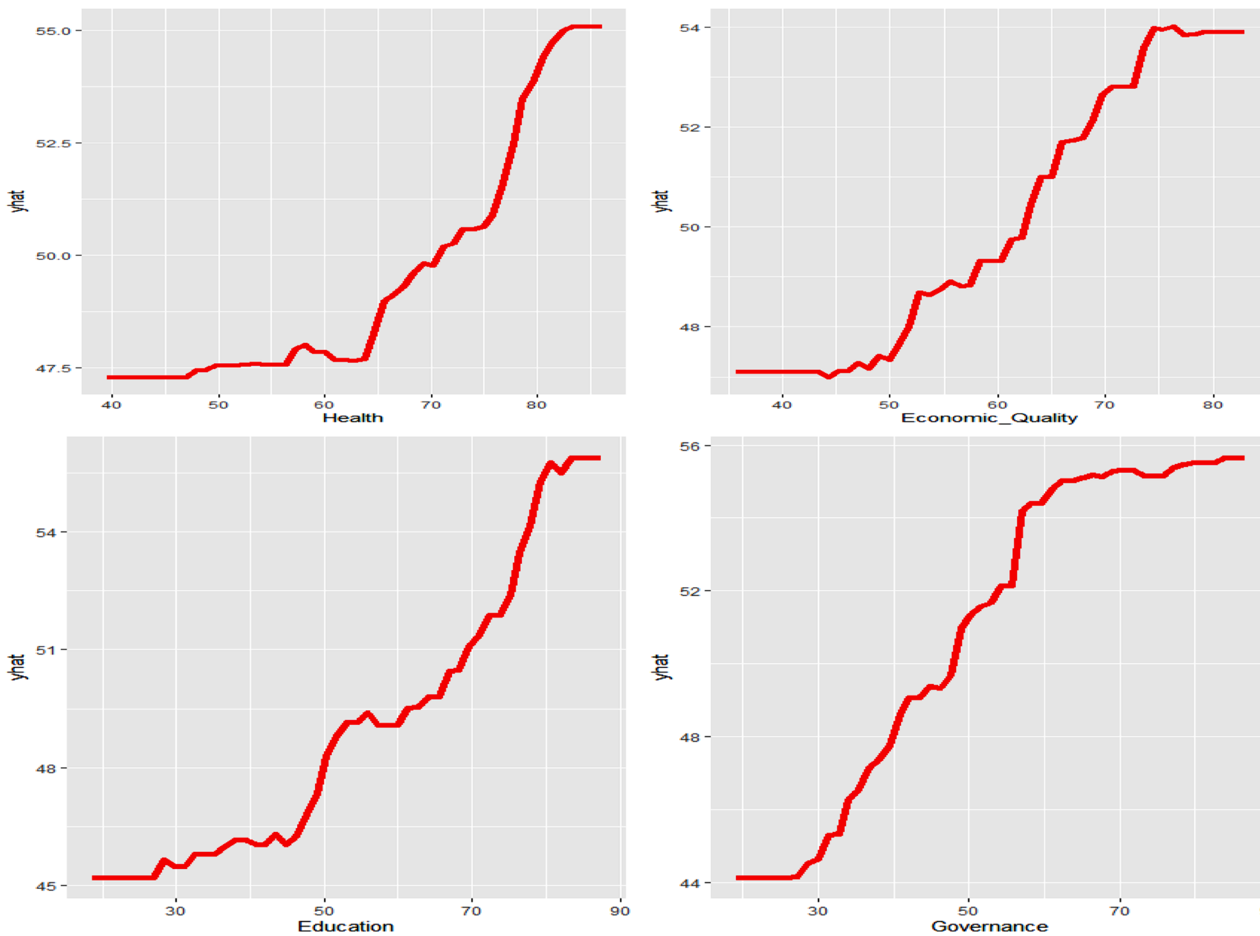

Fig. 4. Partial dependence plots for the four most influential variables, depicting the marginal relationship between entrepreneurial opportunity and the most important factors. PDPs show the effect a feature has on the outcome of the CatBoost model.

$$R^2 = \frac{\sum_{h=1}^{N}\left(\widehat{Y}_h - \overline{Y}_h\right)^2}{\sum_{h=1}^{N}\left(Y_h - \overline{Y}_h\right)^2}$$

All models were fitted in R (R Core Team, 2017). Table 4 summarizes the results achieved by each technique applied according to the different evaluation metrics employed. CatBoost models have a high ability to forecast entrepreneurial opportunity ($R^2 \geq 92.7\%$). Additionally, the prediction error of the CatBoost approach is smaller than that of all other evaluated models, with an RMSE value of 2.930 and an MAPE of 0.048. The second method is the random forest, which has the best MAE value of 2.535, followed by support vector regression, with the best MSE. The third method is deep neural networks. Linear regression is the worst performing algorithm, as it contains the highest values of different metrics and the lowest coefficient of determination.

These results reveal that using machines and deep-learning models to analyze databases containing large amounts of data outperforms multiple linear regression techniques. The results also show that the application of advanced models allows accurate forecasts to be obtained. Indeed, high values of R^2 are obtained by the CatBoost model. The empirical results also point out that the superior application of the artificial intelligence technique is perfectly appropriate for forecasting entrepreneurial opportunities.

5. Conclusion

Using an artificial intelligence framework, this study used the ETE to identify and predict the macro-level determinants of entrepreneurial opportunity. Our empirical analysis aimed to examine the proposition of this theory at the country level and clarify the underlying issues that lead to contradictions in the results of previous literature. Our empirical analysis, based on multiple linear regression and machine-learning models, has provided important findings. First, we found that entrepreneurial opportunity is positively determined by education, governance, health, economic quality, natural environment, and social capital. Second, we explored the potential of using machine- and deep-learning approaches to achieve the aims of this study. The results demonstrate that the use of a CatBoost model and other machine learning techniques is very promising. The numerical results indicate that the CatBoost model performs better than linear approaches. The results of this model show that education and governance quality are the most important factors in predicting entrepreneurial opportunity.

Based on the ETE, our empirical analysis extends the existing entrepreneurship literature on the macrolevel determinants of entrepreneurial opportunity. Despite its theoretical and methodological contributions, our empirical model leads to policy and managerial implications.

The study’s findings also have important managerial implications. First, when entrepreneurs identify local opportunities, but before deciding to exploit them, they should reassess the situation based on a careful study of certain macroeconomic characteristics of their country (for example, economic quality, governance, safety and security). Such an assessment would help these people assess whether conditions at the national level would support or limit the exploitation of opportunities. In other words, entrepreneurs must be aware of the macroeconomic

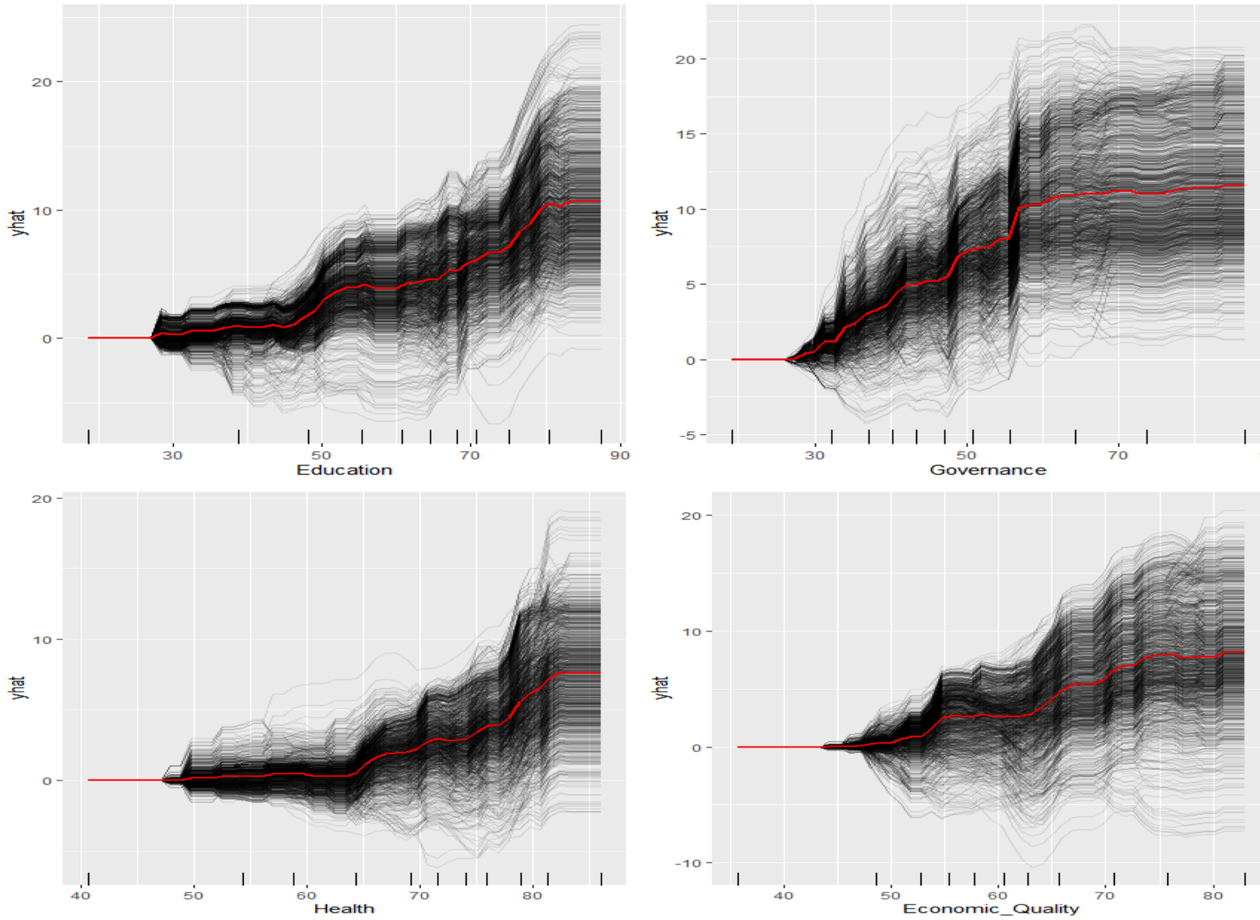

Fig. 5. C-ICE curves (black curves) and their average (red curve) depicted using the CatBoost model. Each curve corresponds to a different observation, and the corresponding line shows how varying the observation's at-issue feature value affects the model's prediction.

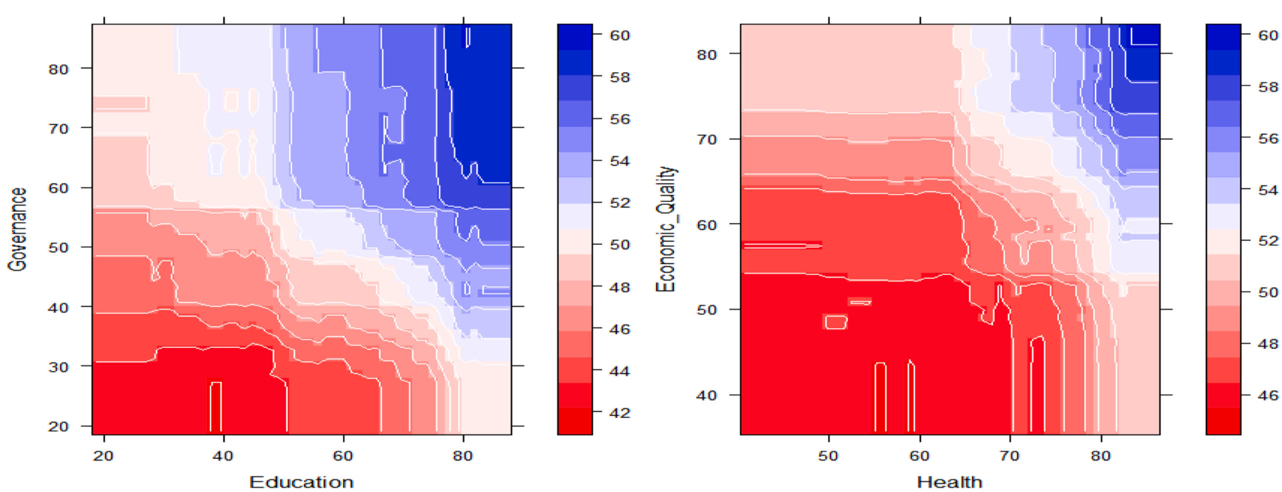

Fig. 6. Two-variable partial dependence plots for the CatBoost model.

determinants of their own country and harness these determinants to strengthen their capacity to assess opportunities. Second, potential entrepreneurs from countries with constraining macroeconomic conditions might consider establishing international collaborations or, more radically, relocating and starting their business elsewhere in countries with macroeconomic conditions more favorable to this type of business.

Various implications for policy-makers emerge from our research. Countries with macrolevel characteristics associated with low rates of entrepreneurial opportunities should focus on five factors (education, governance, health, economic quality, and natural environment). National governments wishing to increase entrepreneurial opportunities should promote their human capital stock, first by improving access to education. This would allow citizens to develop their potential and contribute productively to their society. In addition, the human capital stock enhances research and development and improves the level of knowledge in society. Second, public initiatives should strengthen all

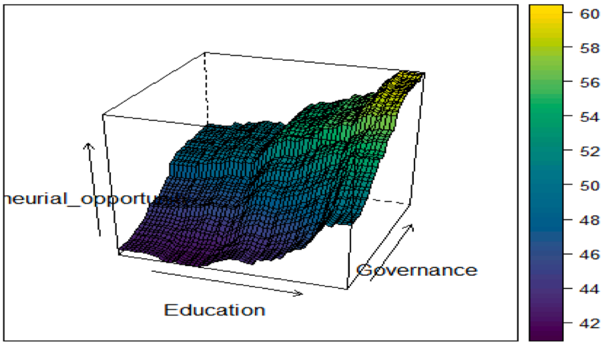

Fig. 7. Two-variable partial dependence plots using a 3D surface for the CatBoost model.

Table 4
Machine-learning model performance on the testing dataset.

	RMSE	MSE	MAE	MAPE	R^2
CatBoost	2.930	10.782	2.878	0.048	0.927
DNN	4.900	26.414	3.869	0.080	0.753
NN	10.816	117.002	8.542	0.174	0.207
RF	3.310	10.957	2.535	0.053	0.916
SVR	3.920	17.556	3.012	0.063	0.858
LR	13.116	172.034	10.318	0.214	0.029

governance-related processes (effective and accountable government, fair elections and political participation, the rule of law, democracy, fight against corruption). Third, the aim should be to achieve stable economic quality (structural policies, economic satisfaction and expectations, distribution of prosperity, commitment, quality and diversity of production), a sound health infrastructure, and a clean natural environment (land and quality of the sea and air).

Regarding future studies, the results achieved in this study could be improved upon if other predictive variables were included, keeping in mind that studies should analyze the predictive performance of more advanced machine-learning models. Future studies could also analyze the microlevel factors that influence entrepreneurial opportunity. Future entrepreneurship researchers should participate in AI-based research, as AI techniques offer an opportunity to promote theory building and testing with rigor and relevance. Therefore, scholars should make greater efforts to enhance the use of these models in their entrepreneurship research.

Short bios

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Author statement

We the undersigned declare that this manuscript is original, has not been published before and is not currently being considered for publication elsewhere.

We confirm that the manuscript has been read and approved by all named authors and that there are no other persons who satisfied the criteria for authorship but are not listed. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

We understand that the Corresponding Author is the sole contact for the Editorial process. He is responsible for communicating with the other authors about progress, submissions of revisions and final approval of proofs.

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