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# PROFILING NASCENT ENTREPRENEURS IN CROATIA - NEURAL NETWORK APPROACH

## ABSTRACT

A significant body of research has been conducted to identify the most important characteristics of nascent entrepreneurs. The aim of this paper is to create a model for recognizing nascent entrepreneurs in Croatia, using the Global Entrepreneurship Monitor (GEM) data for 2014. In this research, the artificial neural networks were used as a machine learning method which enabled the recognition of nascent entrepreneurs, as well as the selection of most important variables and profiling. The suggested model includes variables that describe examinees' attitudes, skills and demographic characteristics, while the binary output variable identifies a nascent entrepreneur. In addition to testing the accuracy of the suggested model, the contribution of this paper lies in the profiling of nascent entrepreneurs in Croatia. This model could be a valuable tool for the government and entrepreneurship support institutions in creating policies and programmes based on recognizing the most important features of nascent entrepreneurs in order to improve entrepreneurial ecosystems.

**Keywords:** Nascent entrepreneurs, GEM, neural network, modelling

## 1. Introduction

An extensive number of studies point to the positive impact of entrepreneurship on economic growth (Birch<sup>1</sup>, 1979; Carree, Thurik, 2003; Neumark et al., 2008; Haltiwanger et al., 2010). Hence, it is important to identify common characteristics of new entrepreneurs in order to create and improve a fostering entrepreneurial ecosystem. Creating

a new venture and becoming an entrepreneur is a process. According to Wagner (2006), the process begins when one or more persons start to commit their time and resources to founding a business. People who put an effort into creating a new business are called nascent entrepreneurs. The Global Entrepreneurship Monitor (GEM Global Report 2016/2017:21)<sup>2</sup> defines nascent entrepreneurs as "those who have committed resources to starting

a business, but have not paid salaries or wages for more than three months". According to this definition, the nascent entrepreneur is observed as a construct variable of two questions: 1) Are you, alone or with others, currently trying to start a new business, including any self-employment or selling any goods or services to others, and 2) Has the new business paid any salaries, wages, or payment in kind, including your own, for more than three months (GEM Dataset 2014)<sup>3</sup>.

Numerous studies have been conducted to identify the most important individual characteristics of nascent entrepreneurs such as age, gender, region and education (Reynolds, 1997; Delmar, Davidsson, 2000; van Stel et al., 2003; Arenius, Minniti, 2005; Wagner, 2006; Nagy et al., 2010). Besides those individual attributes, researchers also looked at individual perceptions of nascent entrepreneurs such as perceived opportunities, capabilities, fear of failure and also their perception of social values related to entrepreneurship (Arenius, Minniti, 2005; Kolveid, Isaken, 2006; Hindle, Klyver, 2007; Wagner, 2006; Bosma et al., 2012; Wyrwich et al., 2016). This research mostly used standard statistical methods for developing profiles of entrepreneurs, including the profile of nascent entrepreneurs. However, in order to advance the accuracy of developing profiles of entrepreneurs, a more advanced and more robust methodology would be welcome.

In recent years, machine learning methods have become interesting when dealing with large amounts of data. In this research, artificial neural networks were used as a machine learning method, which made it possible to recognize nascent entrepreneurs and identify their most important characteristics, thus enabling their profiling.

The aim of this paper is to create a model for recognizing nascent entrepreneurs that will assist in profiling nascent entrepreneurs in Croatia using the Global Entrepreneurship Monitor (GEM) data for 2014, in order to test a new methodological approach in entrepreneurship research. It is expected that this model can help policy makers in creating new or reshaping existing policies concerning new venture creation. Policy changes can significantly contribute to the improvement of entrepreneurial ecosystem in Croatia, which is necessary to change the consistently low scores received for many of its components in some of the most relevant international reports.

## 2. Review of previous research

Entrepreneurship and entrepreneurs have been an interesting research topic in recent decades. Many researchers explore the characteristics of people that are trying to set up a new business (nascent entrepreneurs). As Reynolds (1997) stated, the concept of entrepreneurial behavior clearly implies attempts to start new ventures and does not require that every attempt is successful. Lueckgen et al. (2004), Acs et al. (2005)<sup>4</sup>, Wagner (2006) and many others agree on the definition that nascent entrepreneurs are people who are (alone or with others) actively engaged in creating a new venture and who expect to be the owner(s) or part owner(s) of such a venture.

Both economic and non-economic factors can influence the rate of nascent entrepreneurs (van Stel et al., 2003). Therefore, nascent entrepreneurs differ in many aspects, but what are their common characteristics? Many studies have looked into the demographic factors of nascent entrepreneurs such as age, gender and education level. Reynolds (1997) states that the presence of nascent entrepreneurs in the age group between 25 and 34 years is more than three times higher than in the remaining age groups. He also notices that the relationship between the decision to start a business and age has a bell shape (Reynolds, 1997). Similarly, van Stel et al. (2003) point out that prevalence rates of nascent entrepreneurship are highest in the age group between 25 and 34, though there is a tendency towards startups at even younger age. The probability of becoming an entrepreneur initially rises with age (up to 30 or 35), to descend gradually and continually later (Reynolds, 1997, cited in Alcalde et al., 2002).

Nagy et al. (2010) conducted a research using GEM Adult Population Survey database for 2007 and 2008 to reflect upon the differences between four eastern European countries (Croatia, Hungary, Romania and Serbia). Analyzing the entrepreneurial profile, they stated that the early-stage entrepreneur in 2007 and 2008 is a male, aged between 25 and 34 years in all countries, except for Serbia, where the most frequent age category is 35-44 years. Delmar and Davidsson (2000) say that women participation is negatively associated with nascent entrepreneurship because men are more likely to have the intention to start a firm than women. There were differences in reasons for career choice by gender. Males (entrepreneurs and non-entrepreneurs) rated financial success and innovation higher than females (entrepreneurs and non-entrepreneurs) as a

reason for choosing an entrepreneur career (Carter et al., 2003). The gender divide is particularly wide in southern Europe while in the US the gap is much smaller (Davidsson, 2006). On the contrary, Capelleras et al. (2013) found that gender does not seem to have any significant impact on the likelihood of becoming a nascent entrepreneur. Interestingly, the gender effect is stronger and more significant as long as the model does not include variables for human, social, and financial capital. If women have some managerial or small firm experience, or if their parents were self-employed, they do not have a significantly lower likelihood of being a nascent entrepreneur (Mueller, 2006).

Research results related to nascent entrepreneur's level of education vary. A study conducted on a Swedish sample showed that nascent entrepreneurs attained on average a higher educational level than those in a control sample (Delmar, Davidsson, 2000). However, an OECD<sup>5</sup> study based on data from fourteen countries showed that higher education level tends to correlate with a smaller proportion of self-employment (Uhlener et al., 2002). Capelleras et al. (2013) showed that adults and higher educated people are less likely to become nascent entrepreneurs and individuals who are currently employed are more likely to start a new business. Using a German sample, Mueller (2006) found that work and previous self-employment experience are more relevant than formal education for the prospect of being a nascent entrepreneur. In a research done by Nagy et al. (2010) it was shown that the educational level of early-stage entrepreneurs is significantly higher in Romania and Hungary than in Croatia and Serbia. Bosma et al. (2012) suggested that many entrepreneurs believe that their decision to start a new business and the development of that business have been influenced by others, often entrepreneurs, regardless if they are famous entrepreneurs, former colleagues or family members. Intentions for new business creation are stronger when the degree of self-efficacy grows due to the presence of entrepreneurial role models and when the influences come from several close relatives (Fayolle et al., 2006, cited in Muofhe, Du Toit, 2011).

Other studies focus on individual perceptions of nascent entrepreneurs such as perceived opportunities, capabilities, knowledge, and risk attitudes, primarily fear of failure. Wyrwich et al. (2016) indicate that individual perception of entrepreneurship is an important determinant for subsequent entrepreneurial activity. Jackson and Rodkey (1994) argue that attitude towards entrepreneurship is an

important aspect which predicts potential entrepreneur in future (cited in Pihie, Akmaliah, 2009). When reflecting upon the differences between four eastern European countries (Croatia, Hungary, Romania and Serbia), Nagy et al. (2010) state that entrepreneurship, as a career of choice, is viewed positively in each country. Unlike demographic and economic characteristics, perceptual variables and their impact on entrepreneurship (such as perception of opportunities, own capabilities, intentions and fear of failure) have received less attention from economists (Arenius, Minniti, 2005). An increasing number of scholars agree that opportunity perception is the most distinctive and fundamental characteristic of entrepreneurial behavior (Kirzner, 1973, 1979; Shane, 2000, 2003; Baron et al., 2006). Wagner (2006) states that the share of nascent entrepreneurs in the total population is more than three times higher for those who perceive a good opportunity for business compared to those who do not. Arenius and Minniti (2005) view fear of failure as the perceived risk of experiencing failure and its consequences when engaging in entrepreneurship. Stuetzer et al. (2014) found that individuals who express fear of failure have low probability of having start-up intentions.

Hindle and Klyver (2007) explored the influence of mass media on national entrepreneurial participation rates using GEM data for 37 countries for period of 4 years (2000 to 2003). They found that stories about successful entrepreneurs, presented in mass media, were not significantly associated with the rate of nascent (opportunity searching) or the rate of actual (business activities commenced no more than 3 months before) start-up activity. Still, there was a significant positive association between the volume of entrepreneurship media stories and a nation's volume of people running a new business.

In all the reviewed and presented research papers standard statistical methods were used in order to determine characteristics of nascent entrepreneurs, such as univariate analysis, ANOVA, correlation, logistic regression models, and automatic interaction detection analysis.

### 3. Methodology and data

This paper presents the results of using a neural network approach in testing whether demographic characteristics, individual traits, capabilities and perception of the cultural and social values related to entrepreneurship are important in recognizing the nascent entrepreneurial behavior.

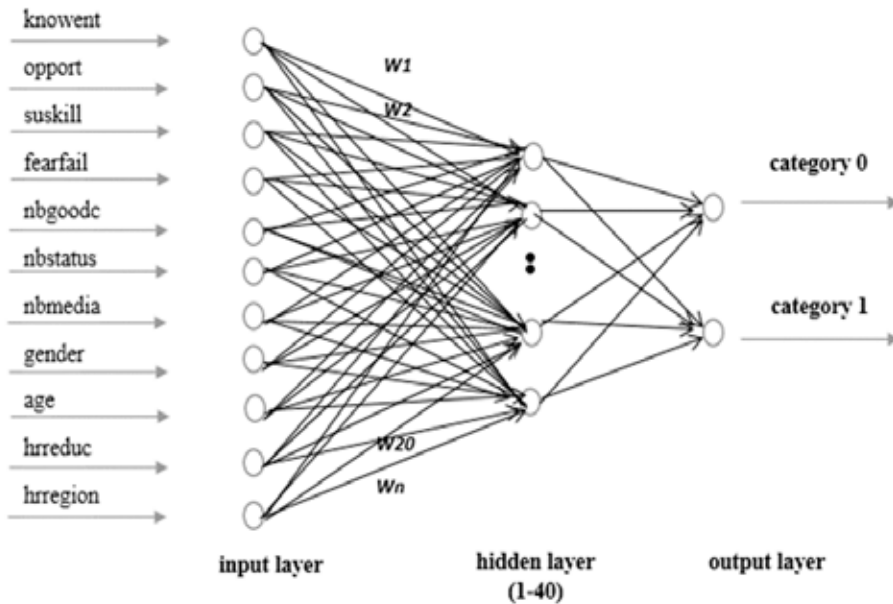
### 3.1 Applied methodology

Artificial neural network (ANN) is a machine learning method that has lately become more important in science, especially in terms of the Big Data concept where this method allows decision making based on business predictive analytics. The basic idea behind this method is to imitate a biological neural network in the human learning process. However, the concept itself is not new, having been developed over seventy years ago. The first artificial neural network was a single-layer neural network called the Perceptron. Due to some limitations, it was not successful in practice and neural research was left on the sidelines. A breakthrough in neural network research was the development of the multilayer perceptron (MLP) network in 1974 and the backpropagation algorithm in 1986. Nowadays,

neural network methodology can be used for different types of problems in different areas such as finance, health and medicine, engineering and manufacturing, marketing etc. (Paliwal, Kumar, 2009).

Artificial neurons have a crucial role in the neural network concept. An artificial neuron can be described as a processing unit or variable that receives weighted input from other variables, then transforms the input according to an activation function, and sends the output to other variables. In neural network methodology, *weights* ( $w_1, w_2 \dots w_n$ ) represent a real number that expresses the strength of connections between neurons (Nielsen, 2015). The neural network is a result of connecting a large number of neurons arranged into layers. A typical structure of a multilayer perceptron neural network (MLP) has three layers (Figure 1).

Figure 1 Topology of neural network models (using GEM variables)



Source: Authors

Figure 1 presents a multilayer perceptron neural network (MLP) architecture of the neural network model presented in this paper. The input layer represents the predictor variable in the network, where each neuron corresponds to each predictor variable (Finlay, 2014). The second layer is a hidden layer

where each neuron  $j$  receives the weighted sum of all  $x_i$  values as the input (Zekić Sušac et al., 2010). This calculation is repeated for each hidden neuron  $j$ . The output  $y$  in the hidden layer in neuron  $j$  is computed by (Masters, 1995):

$$y_j^{(h)} = f\left(\sum_{i=1}^n w_j x_i\right), \quad j = 1, 2, \dots, m \quad (1)$$

where  $f$  represents the activation function. An activation function can be logistic, tangent hyperbolic, exponential, linear, step, or other type. Different activation functions were used in the process of developing the model. The output layer presented in Figure 1 consists of two neurons where neuron valued as 1 represents *Nascent entrepreneurs*, and neuron valued 0 represents all other respondents.

The process of finding weight values that cause the minimum network error is called the learning process. An error indicates the need to change network parameters in order to improve performance. The error is used to adjust the weights of the input vector according to a learning rule (Zekić Sušac et al., 2010). A learning rule is a procedure for modifying the weights and biases of a network (Hagan, 1996). One of most frequently used learning rules is the Delta rule (Masters, 1995).

Multilayer perceptron (MLP) network can use various algorithms to minimize the error, such as Gradient descent (backpropagation), Conjugate gradient descent, Quasi-Newton, Broyden-Fletcher-Goldfarb-Shanno and others, depending on the user's preference.

After developing a neural network model, it is necessary to conduct network performance evaluation which depends on the type of problems: classification or regression. The quality of a classification model can be assessed through discrimination and calibration. Discrimination measures how well the two classes in the data set are separated, while calibration determines how accurate the model probability estimate  $f(x; \alpha)$  is to the true probability  $P(y/x)$  (Dreiseitl, Ohno-Machado, 2002). In this paper, we are dealing with the classification type of problems and calibration has been used as a measure for model evaluation. Network performance is evaluated by the classification rate and it is measured according to:

$$\text{Total classification rate} = \frac{\text{number of correctly classified cases}}{\text{total number of cases in sample}} \quad (2)$$

### 3.2 Used data

The data used in creating the model is from the Global Entrepreneurship Monitor (GEM) survey, the most extensive study of entrepreneurship in the world. GEM began in 1999 as a project of Babson College (USA) and the London Business School (UK) with the intent to determine why some countries are more entrepreneurial than others. The GEM survey is based on collecting primary data through an Adult Population Survey of at least 2,000 randomly selected adults (18–64 years of age) in each economy. In addition, national teams collect expert opinions about components of the entrepreneurship ecosystem through a National Expert Survey (NES).

The GEM APS dataset from 2014 survey, which was used in this paper, contains 1,989 respondents from Croatia aged between 18 and 64. The input space consists of 11 input variables describing demographic data (e.g. age, gender and region), individual perceptions (e.g. perceived opportunity, perceived own capability in terms of knowledge and skills) and perception of social values related to entrepreneurship (e.g. perception of how media is contributing to forming supportive social values to entrepreneurship). The output variable (*nascent*) is expressed in two categories. Category 1 represents *nascent entrepreneur* as a person who has committed resources to starting a business, but has not paid salaries or wages for more than three months. Category 0 represents *all other* respondents (persons that are currently not active in trying to start a new business as well as the ones who already have an established business<sup>6</sup>). All variables and their descriptions are presented in Table 1.

**Table 1 Variables included in the neural network model<sup>7</sup>**

	Variable code	Description of variable – GEM question
Input variables	Age	Age: <i>What is your current age (in years)?</i>
	Gender	Gender: <i>What is your gender?</i>
	hrregion	Region: <i>Survey vendor to provide the region in which the respondent lives</i>
	hrreduc	Education: <i>What is the highest level of education you have completed?</i>
	knowent	Personally knowing someone who started a business in the past two years: <i>Do you know someone personally who started a business in the past two years?</i>
	oport	Perceived opportunity for starting a business in the area in which the respondent lives in the period of next six months: <i>In the next six months, will there be good opportunity for starting a business in the area where you live?</i>
	suskill	Perceived knowledge, skills and experience required to start a new business: <i>Do you have the knowledge, skill, and experience required to start a new business?</i>
	fearfail	Would fear of failure prevent the respondent from starting a business: <i>Would fear of failure prevent you from starting a business?</i>
	nbgoodc	Perception of starting a new business as a desirable career choice in the respondent's country: <i>In my country, most people consider starting a new business a desirable career choice.</i>
	nbstatus	Perception of people who are successful at starting a new business as the ones with a high level of status and respect: <i>In my country, those successful at starting a new business have a high level of status and respect.</i>
	nbmedia	Perception of media coverage of successful entrepreneurship stories: <i>In my country, you will often see stories in the public media and/or internet about successful new businesses.</i>
Output variable	nascent	<b>Category 1</b> - nascent entrepreneur: Construct of <b>bstart</b> (Are you, alone or with others, currently trying to start a new business, including any self-employment or selling any goods or services to others?) and <b>suwage</b> (Has the new business paid any salaries, wages, or payment in kind, including your own, for more than three months?) <b>Category 0</b> - represents all other respondents

Source: GEM Database (2014)

Neural networks have three phases of work: a training phase for network learning, a testing phase for parameter optimization and a validation phase for

model evaluation. Therefore, the total sample of 1,989 respondents was divided into three subsamples (Table 2).

**Table 2 Sampling procedure**

Subsample	Output category		Total no. of cases
	0 <i>All others</i>	1 <i>Nascent</i>	
Train	63	63	126
Test	21	21	42
Validation	1,800	21	1,821
<b>Total</b>	<b>1,884</b>	<b>105</b>	<b>1,989</b>

Source: Authors

Table 2 shows class unbalance from the used data set. Due to a large number of cases in category 0 (All others) and the significantly smaller number of cases in category 1 (Nascent), equal distribution of cases has been kept in subsamples for training and testing. The rest of the cases have been put in the validation sample and used for final testing and evaluation of the model accuracy. In the pre-processing phase, min-max normalization of data was conducted.

#### 4. Results

To find the optimal neural network model, different neural network parameters i.e. architectures, activation functions, and training algorithm were used. 30 neural network architectures were tested

by changing the number of hidden units from 1 to 40 and the activation function in the hidden layer (logistic or tangent-hyperbolic function).

In this research, the output variable is represented as a category (0 and 1) and therefore for error function cross entropy was used. However, different training algorithms (Gradient descent and Broyden-Fletcher-Goldfarb-Shanno (BFGS)) were used. In this paper, a higher classification rate (hit rate) was achieved with the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm.

For evaluation of the model accuracy, the total classification rate (hit rate) was used. Regarding the large number of conducted NN models, only two most accurate neural network architectures are presented in Table 3.

*Table 3 Summary of best results on the validation sample*

Neural network model architecture	Training algorithm	Activation function in the hidden layer	Error function	Total classification rate on the validation sample	Classification rate of category 0 (all others)	Classification rate of category 1 (nascent)
MLP 31-11-2	BFGS	Logistic	Cross entropy	80.10	80.16	75.00
MLP 31-5-2	BFGS	Tangh	Cross entropy	73.12	73.15	70.00

Source: Authors

The comparison of accuracy of the best ANN models (see Table 3) was conducted using a statistical test of difference in proportion. The test produced p-value of 0.003 (N=1,804). The obtained p-value shows that a neural network with a logistic activation function is significantly more accurate than a neural network with tangent activation function.

The neural network model with logistic activation function was selected for further analysis. The architecture of the neural network MLP 31-11-2 consisting of 31 input neurons, 11 hidden neurons and 2 output neurons has produced the best result. The total classification rate of the best model obtained on the validation sample was 80.10%, meaning that the model can predict if someone can be classified as a nascent entrepreneur with 80.10% of accuracy. In addition, the classification rates for each category were calculated. The classification rate for category 0 (all others) was 80.16% and for category 1 (nascent) 75%.

The model accuracy and its stability is highly dependent on the size of the sample and sampling procedure. In order to determine the stability of the model, a k-fold cross-validation procedure was conducted. This procedure splits the total sample randomly into *k* mutually exclusive subsets of approximately equal size (Kohavi, 1995). The stability of this model was tested with a 10-fold cross-validation procedure. The same procedure was repeated 10 times, in each step a different subsample was used for training and for testing. The results were produced on 10 different samples. The results of the random sampling procedure are given in Table 4. It shows that the accuracy and stability of the neural network model depends on the sample structure. The average of 10 neural network results on the validation subsamples was used as the measure of the model's expected accuracy on new data. The observed average accuracy across all samples was 93.96%. This percentage indicates a high level of network stability.

Table 4 Results of the best neural network model in random sampling

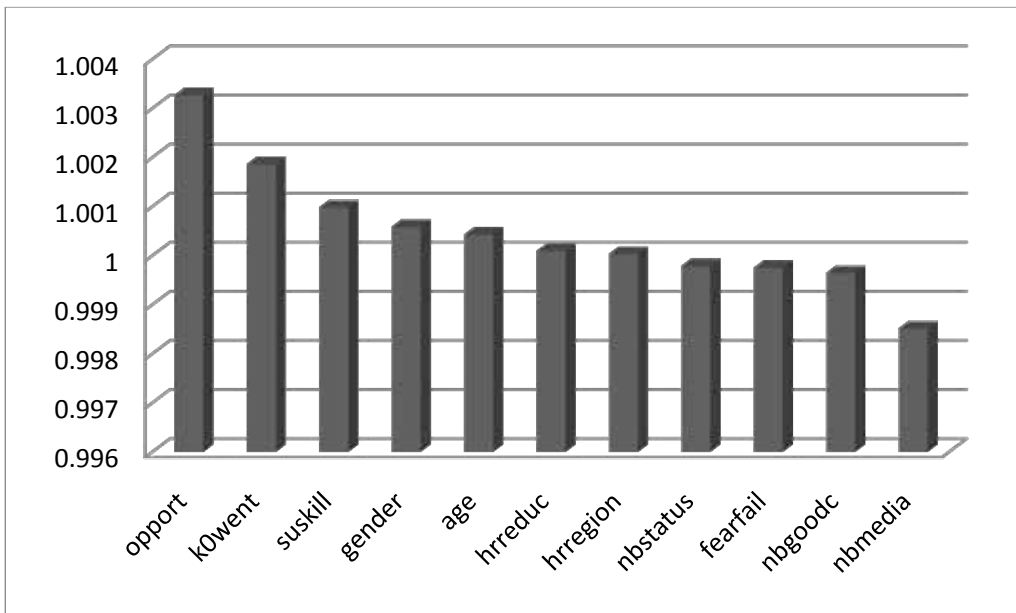
Validation subsample	1	2	3	4	5	6	7	8	9	10	Average
<b>Total classification rate</b>	94.16	92.39	95.69	94.92	92.89	93.91	95.18	95.18	93.15	92.13	<b>93.96</b>

Source: Authors

In the next step, the sensitivity analysis was conducted. Testing of the impact of each particular input variable on the output variable of the model was conducted through sensitivity analysis. An important trait of this method is that the sensitivities are computed one layer at a time, starting from the

output layer and proceeding backwards toward the input layer (Hashem, 1992). In this paper, the sensitivity analysis was performed on each of 10 validation subsamples. The average value of sensitivity coefficient of each input variable is shown in Figure 2.

Figure 2 Sensitivity coefficients of input variables in the neural network model



Source: Authors

The higher sensitivity coefficient means that a certain input variable has a higher impact on the output variable. Sensitivity analysis revealed that perceived opportunity, knowing someone who started a business, as well as skills and experience required to start a new business had the biggest influence on the decision to start a business. Demographic variables, the perception of status and respect of entrepreneurs and the perception of media coverage of successful new businesses have less impact on output variable.

After creation and analysis of the model for recognizing nascent entrepreneurs, the procedure of profiling nascent entrepreneurs was conducted. In order to identify a common profile of nascent entrepreneurs in Croatia, the values of more frequent input variables were extracted. The obtained results show that nascent entrepreneurs in Croatia are mostly men between 28 and 37 years, from the Zagreb region followed by Northern Croatia, with 4-year vocational education. In terms of the perceptive attitudes, they believe that they have the



necessary skills and knowledge for starting a business and they do not have fear of possible failure. They do not have an entrepreneur as a role model and they believe that most people in their country consider that starting a new business is a desirable career choice. However, they do not believe there will be a good opportunity for starting a business in next six months in the region in which they live. This is surprising and contrasting to previous findings in the literature (e.g. Wagner, 2006). Furthermore, nascent entrepreneurs in Croatia believe that the media do not often report on successful new businesses, whereas successful entrepreneurs do have a high level of status and respect. The extraction of important characteristics on our dataset are in line with the previous findings in literature except the perception of opportunities, which is in contrast to previous findings of Wagner (2006). It can be found that subjective perceptions about one's own skills, likelihood of failure, existence of opportunities, and knowledge of other entrepreneurs, are all highly correlated with the decision to start a new business.

## 5. Discussion and conclusion

In this paper, a neural network model for recognizing nascent entrepreneurs was created using the Global Entrepreneurship Monitor (GEM) 2014 data for Croatia. The created model includes variables that describe respondents' perceptive attitudes, skills and demographic characteristics. Several neural network architectures were tested by changing the activation function and the number of hidden neurons. The most successful model was selected on the basis of the total classification rate, and the  $k$ -fold cross-validation procedure showed that the average accuracy of the model across ten subsamples was 93.96%. The obtained results show that the neural network method can be used for recognizing nascent entrepreneurs. Our model allowed for the profiling of nascent entrepreneurs in Croatia, which was presented in the result section of the paper.

Further research should move towards improving the presented model and expand the profile of nascent entrepreneurs. It would be advisable to increase the number of cases that represent nascent entrepreneurs or to use a different approach for handling unbalanced dataset (oversampling, synthetic sampling etc.) as well as to include additional variables in the model.

Previous research has shown that profiling of nascent entrepreneurs was mostly conducted by standard statistical methods like univariate analysis, ANOVA, correlation and logistic regression models (Arenius, Minniti, 2005; Wagner, 2006; Nagy et al., 2010; Stuetzer et al., 2014). However, for further research it is recommended to compare the model presented here with other machine learning methods (e.g. decision trees).

The expected contribution of this paper is in testing a new methodological approach and adding robustness to the methodology of entrepreneurship research. Another expected contribution is in empirical evidence on nascent entrepreneurs in Croatia.

Using new methods of analysis on the existing data can cast a new light and give new perspectives for researchers and practitioners in the field of entrepreneurship. This could also be useful for entrepreneurship support institutions to assist them in recognizing the most important features of nascent entrepreneurs to create measures that could help improve entrepreneurial ecosystems. The model presented in this paper can assist policy makers when designing policies addressed to nascent entrepreneurs. Additionally, it could be used in shaping customized policies, rather than one-size-fits-all policy. Customized policies, in the long run, could contribute to a better distribution of governmental support focusing more on those groups of nascent entrepreneurs who really need it. Apart from the financial aspect, this model could be the base for developing new government programs oriented towards entrepreneurship such as vouchers for using the services of research institutes or industrial designers to create better-designed products.

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## PROFILIRANJE PODUZETNIKA POČETNIKA U HRVATSKOJ KORIŠTENJEM NEURONSKIH MREŽA

### SAŽETAK

Brojna istraživanja provedena su kako bi se identificirale najvažnije karakteristike poduzetnika početnika. Cilj ovog rada je kreiranje klasifikacijskog modela koristeći podatke svjetskog istraživanja Global Entrepreneurship Monitor (GEM) za 2014. godinu. U radu su korištene neuronske mreže, metoda strojnog učenja koja omogućava prepoznavanje poduzetnika početnika i njihovih karakteristika. U model su uključene ulazne varijable koje opisuju stavove ispitanika, njihove vještine i demografske karakteristike, dok binarna izlazna varijabla identificira poduzetnika početnika. Osim točnosti ispitivanja klasifikacijskog modela, doprinos ovog rada je u profiliranju poduzetnika početnika u Hrvatskoj. Predloženi model može biti vrijedan alat za institucije državne uprave i poduzetničke potporne institucije kao pomoć u oblikovanju politika i programa temeljenih na prepoznavanju najvažnijih značajki poduzetnika početnika, čime se doprinosi poboljšanju poduzetničkog ekosustava.

**Ključne riječi:** poduzetnici početnici, GEM, poduzetnički ekosustav, neuronske mreže, modeliranje