Assessment of Investment Attractiveness in European Countries by Artificial Neural Networks: What Competences are Needed to Make a Decision on Collective Well-Being?

Jurgita Bruneckiene [1,*], Robertas Jucevicius [1], Ineta Zykiene [1], Jonas Rapsikevicius [1] and Mantas Lukauskas [2]

[1] School of Economics and Business, Kaunas University of Technology, 44239 Kaunas, Lithuania; robertas.jucevicius@ktu.lt (R.J.); ineta.zykiene@ktu.lt (I.Z.); jonas.rapsikevicius@ktu.lt (J.R.)

[2] Faculty of Mathematics and Natural Sciences, Kaunas University of Technology, 44239 Kaunas, Lithuania; mantas.lukauskas@ktu.lt

* Correspondence: jurgita.bruneckiene@ktu.lt; Tel.: +370-37-300-550

Abstract: A rich volume of literature has analysed country investment attractiveness in a wide range of contexts. The research has mostly focused on traditional economic concepts—economic, social, managerial, governmental, and geopolitical determinants—with a lack of focus on the smartness approach. Smartness is a social construct, which means that it has no objective presence but is "defined into existence". It cannot be touched or measured based on uniform criteria but, rather, on the ones that are collectively agreed upon and stem from the nature of definition. Key determinants of smartness learning—intelligence, agility, networking, digital, sustainability, innovativeness and knowledgeability—serve as a platform for the deeper analysis of the research problem. In this article, we assessed country investment attractiveness through the economic subjects' competences and environment empowering them to attract and maintain investments in the country. The country investment attractiveness was assessed by artificial intelligence (in particular, neural networks), which has found widespread application in the sciences and engineering but has remained rather limited in economics and confined to specific areas like counties' investment attractiveness. The empirical research relies on the case of assessing investment attractiveness of 29 European countries by the use of 58 indicators and 31,958 observations of annual data of the 2000–2018 time period. The advantages and limitations of the use of artificial intelligence in assessing countries' investment attractiveness proved the need for soft competences for work with artificial intelligence and decision-making based on the information gathered by such research. The creativity, intelligence, agility, networking, sustainability, social responsibility, innovativeness, digitality, learning, curiosity and being knowledge-driven are the competences that, together, are needed in all stages of economic analysis.

Keywords: investment attractiveness; artificial intelligence; neural networks; smartness; competences; comprehensive decision on collective well-being

1. Introduction

Globalisation, the fourth industrial revolution, a rapidly changing environment, and consumer needs lead to increasing competition among companies. They compete for ideas, products or services, consumers, employees, technologies, projects, markets, and so on. To stay competitive, companies must find novel and smart ways to compete and remain competitive nationally and internationally

in the long term. Foreign direct investment is one of the means to enhance a company's competitiveness and the well-being of the whole country. Individuals' life satisfaction is related to the economic situation in a country. Companies in countries attracting more foreign direct investment are characterised by higher levels of competitiveness, innovation, and technological development [1,2]. By enhancing investment attractiveness, countries themselves contribute to the increase of companies' competitiveness, sustainable economic development, attraction of knowledge, technologies and innovation, creation of infrastructure, and emergence of related and service-based businesses [3]. The positive impact of foreign direct investment justifies the importance of the smart formation of a country's investment attractiveness at a national strategic level and correct forecasting of incoming investment. Countries, which are able to maintain and model future foreign direct investment, can more accurately plan their budgets, form strategic development paths, and diversify and more effectively manage the risks and adverse effects relating to investment exit.

Under the current economic challenges and the fourth industrial revolution, where technologies are inevitably integrated in critical infrastructure, economic development must be not only technology driven but also have a particular focus on sustainability as well as soft capacities, such as entrepreneurship, innovation, and learning. These changes require rethinking policy in regard to the country's investment attractiveness. The formation of investment attractiveness based on the classification of economic, legal, political, technological, geographical, and infrastructural factors is the most commonly used in practice by many countries. New challenges for economies are changing factors and their influence on investment attractiveness. The use of dynamic capacities, such as intelligence, agility, knowledge and innovation, learning, networking, and so on, increasingly creates an advantage for the country or the company and is the base for creation of smart strategies. The consideration of the concept of investment attractiveness under the approach of smartness, which corresponds to the modern economic development tendencies and trends of contemporary business, is a new way of thinking and discussing in scientific literature.

The smartness approach has been strongly developed and led by business practitioners and policy makers (e.g., Europe 2020, Horizon 2020, and Smart specialization strategies of the EU members). The smartness concept quite often is used under the context of urban planning and smart cities, smart specialization strategies, or general development of smart socio-economic systems. Although, integration of the smartness concept, which covers the extensive use of technologies with related soft capacities, to countries' investment attractiveness is missing. Therefore, this approach does not analyze usual infrastructure, economic, or institutional frameworks, but rather, it focuses on smartness determinants, such as intelligence, innovation, knowledge, agility, learning, networking, digitality, and sustainability. Analysis of investment attractiveness through the smartness approach might ensure its adequacy to time changes and economic challenges.

The major issue faced by the scientists analysing multifunctional concepts is the abundance and diversity of factors determining them. Because of the networked interaction and the quantity of factors determining foreign direct investment, the assessment becomes a complex task and a major challenge to both the scientists, as regards the reliability and interpretation of results, and to the strategists, as regards the correctness of result-based conclusions and decisions. In the event of large data flows and complicated relationships among them, the use of artificial intelligence is one possible way for a scientist or strategist to smartly identify economic problems, their sources, and their challenges. This allows for a quicker and more accurate answer (avoiding human error) and justification for the formulation of economic conclusions and decisions. For this reason, the use of artificial intelligence in the economy becomes an important as well as essential aspect.

The use of artificial intelligence and new methodological research frameworks in economic analysis not only extends the limitations and opportunities of research, but it also poses new challenges to the researcher himself and to the user of economic research findings, the correctness and timeliness of whose decision more or less directly influences the competitiveness and investment attractiveness of a company and a country and, at the same time, the well-being of the entire population. The increasing use of artificial intelligence in economic analysis requires and stresses the

need of new competences for work with it. New competences are needed not only to perform the research but also to interpret the research findings for decision-making.

The aim of this paper is to define the countries' investment attractiveness under the approach of smartness and identify the key competences that are important for work with artificial intelligence and decision-making based on the information gathered by such research.

The research methods employed are systematic, comparative, and logical analyses of the scientific literature, based on the methods of comparison, classification, systematization, and generalisation; cluster data analysis; and models of artificial neural networks.

The paper is organised as follows: Section 2 discusses the use of artificial intelligence in decision-making on collective well-being. Section 3 integrates the concept of investment attractiveness with the smartness approach. The next section introduces the main factors and indicators determining a country's investment attractiveness under the approach of smartness. Section 5 presents the results of the empirical study on the assessment of investment attractiveness in European countries using neural networks. The last section of the paper discusses the competences needed for the user of artificial intelligence to adopt decisions on collective well-being, resulting from empirical study, as well as research limitations. The paper ends with conclusions and future research.

2. Artificial Intelligence and Decision-Making on Collective Well-Being

The term artificial intelligence, which is widespread in society and is often associated with technology, accuracy, and optimality, urges thinking about rationality. Its working principle is highly complex, imitating human brain activity. Artificial intelligence is widely used in many areas, from finance, marketing, and economic analysis to medicine and the military industry. Economic papers extensively analyse topics relating to the impact of artificial intelligence on the economy and business [4–7], economic policy, and financial regulation for artificial intelligence [8,9]. Particular attention is paid to the impact of artificial intelligence on productivity [10,11] and interchangeability of jobs [12–15]. Artificial intelligence has been widely used to analyse various economic concepts and problems, for example, in a city smartness analysis [16] prediction of knowledge-hiding behaviour [17] as well as modelling and forecasting [18,19]. The increased use of artificial intelligence in spatial economic analysis is based on its benefits [6,20,21], which include a faster and more accurate answer; a solution to more sophisticated challenges, as methods of artificial intelligence can handle very large quantities of indicators; modelling of dynamic indicators, as algorithms can adapt to newly submitted data and be retrained; and possibilities to predict and model values of indicators; possibilities to analyse each country individually in the context of influence of other countries. The challenges of the use of artificial intelligence in economic modelling are connected with the need of a huge volume of time series, the use of a significant quantity of computer resources and time, and the needed competences to model and interpret the information gained in the synergy with artificial intelligence. For example, machine learning with a teacher requires the prior assignment of training data to classes; thus, expert judgment is required (the expert must determine which class includes the observed observations). Incorrect expert judgments can lead to the wrong process of model development and improper use of these models, as well as obtaining flawed conclusions. Not all algorithms of artificial intelligence, such as artificial neural networks, provide the result of variable interactions. For this reason, the relevant competences of interpreting the results are required.

Artificial intelligence is not enough where the interpretation of results and creativity are needed [22]. Answers are widely sought to what skills and competences are needed for work with artificial intelligence. The biggest attention is payed to hard skills, which are typically job-specific skills and competences that are needed to perform a specific job or task. Usually, hard skills are knowledge of specific software or instruments, specific manual abilities, and so on [23]. The latest research arises with analysis of the importance of soft skills to Industry 4.0—the capacities of individuals to interact with others and the environment (communication skills, problem solving, etc.) [24]. There is the necessity of soft skills in work with artificial intelligence [24–26], including interpersonal skills, personal affirmation, respect, power of ego, empathy, perseverance, spirit of perfection, self-discipline, refined, refining, independence, and creativity. So far, artificial intelligence has no

emotional intelligence in itself. Its possession is the responsibility of the creator of artificial intelligence and of the decision-maker. Commonly, stress on soft skills is laid on personal skills [25,27] and emotional intelligence [28–33], with less emphasis on competences through the smartness approach. Integration of the smartness approach to emotional intelligence lets smart decisions be made. An individual can create and train artificial intelligence in rational decision-making; however, upon setting certain selfish preferences, it will provide us with a rational decision, which is possibly irrational in terms of collective well-being. The trap lies in the preferences set by an individual. Even if artificial intelligence provides a rational decision in terms of collective well-being, perhaps the decision-maker will cause irrationality in the aspect of collective well-being based on his or her individual rationality and philosophy of thinking (e.g., liberal, capitalist, or socialist views). The dominance of human pessimism may burden the improvement of social and economic welfare and, therefore, should be taken into scientific consideration [34]. Rational decisions as well as decisions covering a certain responsibility (i.e., smart decisions) are required from cooperation between man and artificial intelligence.

3. Investment Attractiveness: A Smartness Approach

A country's investment attractiveness is treated as a comprehensive decision on collective well-being because it influences the economy of the whole country. There are both positive [35] and negative aspects of investment attraction to a country (dominance of foreign companies, cultural changes, technological dependence) [36], although scientists more often identify positive impacts [37]. The fact is no longer called into question that investment attraction to a country encourages business development; ensures the adoption of best practices in the areas of management, marketing, and introduction of state-of-the-art technologies; and helps create the requisite infrastructure. Attracted investments have a positive impact on technological upgrades in the country and are important for knowledge transfer [1]. Investments have a positive impact on the country's macroeconomic indicators such as GDP growth [2,38], increase in labour productivity [3,39], export development [36,40], reduction of unemployment [38,41–44], national tax revenue [45–47], and innovation development [48–51]. The flow of investment not only increases the number of the employed but also raises their qualifications. Investments help mobilise economic activities in less developed countries by improving their economic efficiency [52].

Some research studies maintain that economic growth is independent of foreign direct investment (FDI) [37], which suggests that the relationship between FDI and a country's economic growth cannot be assessed unambiguously; however, a positive impact on the national economy and sustainability prevailing in research enables us to treat FDI as a solution to collective well-being and an important measure to encourage a country's economic development, provided that the country has the competences and capacities to effectively manage the risks and adverse consequences associated with the outflow of foreign direct investment. Such a conceptual approach to FDI, involving insights and rational, advanced preparation by preventing or mitigating as much as possible the negative consequences of FDI for the economy, poses new challenges for a country's strategic management, increase of its economic resilience, and for sustainability. In order to ensure this, it is necessary to have timely and up-to-date information on investments and related trends in the country and in the surrounding economies, and forecasts, as accurate as possible, which are important for insights and relevant decision-making.

An important challenge to countries (more in a practical aspect than in a theoretical aspect) is to attract investments because, generally, they do not come automatically. Countries try to create such investment attraction mechanisms [53,54] or such characteristics [55] that make them more attractive compared with other countries. Countries compete for investments by offering investors favourable local conditions or even adapting them to the needs of investors [56]. In the definition of foreign direct investment, the International Monetary Fund emphasised the aim of establishing a lasting interest by the investor in the economy of another country (investment recipient). In order to attract investment to a specific area, its characteristics must be in line with the investor's expectations, based on which he has chosen the specific area for his business start-up or development [55]. The most common

reason for investment is the development of markets [57,58], which reaffirms the relevance of timely information and forecast investment trends in a country at a practical level.

Investor decisions on which the country chooses for investment depend on a number of different factors ranging from the price of the labour force, availability of the requisite competences, the country's geopolitical location, the tax system, intensity of market competition, and political stability in the country [59–61] to lobbying [62,63], managerial discretion [64], clusters, and networking [65]. All these factors are in line with the investment attractiveness concept. A country's investment attractiveness in regard to foreign direct investment is a two-dimensional concept [66–68], consisting of (a) a set of various economic, legal, political, technological, geographical, and infrastructural factors enabling the investor to gain a competitive advantage over his competitors; and (b) the ability of a country to attract new and preserve existing investments, while maintaining its advantage over other countries. Such an approach to a country's attractiveness in regard to foreign direct investment makes it possible to look at attractiveness as a result and a dynamic process together. This means that the country's set (input), forming investment attractiveness in regard to foreign direct investment, attracts FDI (output), which, together with the country's ability to attract new and retain existing investment, creates/maintains the current investment attractiveness for attracting new FDI. That justifies the approach to investment attractiveness as a solution to collective well-being.

Scientific discussion appears [55,69–73] claiming that it is no longer enough to analyze economic development through common development factors. Dynamic competences or capabilities, a concept firstly introduced by Teece et al. [74], are re-gaining importance in modern economy [75,76]. Such a concept suggests that multiple competences are needed for the company to be able to adequately react to the challenges from its external environment. However, more sophisticated approaches are needed in order comply with the growing complexity of the business environment. New thinking is also needed in analyzing and forming a country's investment attractiveness. The concept of smartness may probably be one of such approaches. The growing literature on smartness determinants is inevitably related to the rapid progress of information communications and technologies (ICT) as well as its implementation and digitalization [77–79]. Later, the focus on intelligent management for improving governance and economic efficiency [80] and soft determinants of smartness [71,81] was put. The smartness approach stresses that the smart development of a socio-economic system could be achieved with the wide use of technologies and related soft competencies for empowering them. The use of ICT and digital technologies could solve long-run sustainability problems and transform cities and economies in a broader context [79]. However, scientists highlight the importance of knowledge, agility, and entrepreneurship [72,79]. Bakici et al. [82] justify that the smartness approach is achieved through cooperation and networks among companies, institutions, and the citizens. Such soft factors as entrepreneurship [72,83], learning [71], managerial discretion [64], clusters, and networking [84] are distinguished as the determinants of the smartness approach. From the mid-2000s, the smartness approach started to be applied in the spatial context (i.e., urban planning, smart cities, and regions [78–80,85,86]), which is the methodological base to use this approach on the country level. The smartness approach is used for analysing sustainable development [77,79], competitiveness [72], and a location's attractiveness for business development [55]. However, the investment attractiveness has not been analysed in the context of the smartness approach.

Principles and determinants of the concept of smartness have been grounded on understanding that people are at the heart of any socio-economic system. All decisions are made by humans, and only smart people can make smart decisions. The complexity theory was taken as grounding theory. We suggest that smart social systems be dynamically adaptive to new circumstances, innovative and knowledge-driven, strategically minded, internetworked, and learn and effectively exploit the opportunities offered by the new trends in order to achieve the preferred development objectives [71,81].

A systematic–theoretical comparative analysis of the concepts of smartness and investment attractiveness let us define the determinants of a country's investment attractiveness under the approach of smartness:

- Attractiveness in regard to the intelligence are conditions that form and encourage the abilities of economic subjects to assess the internal and external environment, penetrate the challenges, predict the future, and exploit the opportunities to make the most effective decisions related to investment attractiveness and be at least a step ahead of the competitors;
- Attractiveness in regard to networking and infrastructure are conditions that form and encourage the abilities of economic subjects to create networks and use the opportunities offered by different types of networks and infrastructure for communicating and seeking complex, timely solutions for increasing investment attractiveness;
- Attractiveness in regard to the sustainability are conditions that form and encourage the abilities of economic subjects to make long-term decisions for creating investment attractiveness by combining environmental, economic, socio-cultural, socially responsible, transparent, and honest components;
- Attractiveness in regard to the digitalization are conditions that form and encourage the abilities of economic subjects to make extensive use of information and communication technologies for information, communication, networking, decision-making, and implementation;
- Attractiveness in regard to learning are conditions that form and encourage the abilities of economic subjects and their networks to continuously learn and be empowered by learning for making decisions related to investment attractiveness;
- Attractiveness in regard to agility are conditions that form and encourage the abilities of economic subjects to achieve investment attractiveness decisions by responding promptly to changes caused by external and internal environments; and
- Attractiveness in regard to innovation and knowledge-driven are conditions that form and encourage the abilities of economic subjects to create value and make decisions to enhance investment attractiveness through knowledge, innovation, research, and rethinking.

With an increasing use of artificial intelligence in economic analysis, it is important to identify competences in rational decision-making on collective well-being. This is a prerequisite for ensuring economic sustainability in the long term. The problem analysis relies on the case of assessing investment attractiveness in the integration of smart development theory in European countries by using neural networks.

4. Research Methodology

The theoretical background of the concept is the rationale for the assessment of the investment attractiveness of countries. To create the theoretical background, we used a systematic literature review and followed the main factors of investment attractiveness, which were examined and constructed in the previous research [59–61], and combined them with the smartness approach [55,71,75,81,86]. In this way, we combine traditional economic concepts—economic, social, managerial, governmental, and geopolitical elements (A.T. Kearney Foreign Direct Investment Confidence Index, 2019, WEF, 2019, Global Retail Attractiveness Index, 2019, GFICA index, 2018)— with smartness determinants including intelligence, networking and infrastructure, sustainability, digitalization, learning, agility, innovation, and being knowledge-driven [71,81]. This interrelated structure of the factor model allows us to look at investment attractiveness as a countries' ability to attract and maintain the investments. Such a view lets us analyse the investment attractiveness from the competences of countries' economic subjects for policy making and investment decisions. The novelty of the presented model is the adaption of the smartness approach in investment attractiveness on the country level. Also, the model presented by Snieska et al. [55] was applied to regions within the same country.

Table 1 shows factors and 58 indicators updated with national-level indicators.

Table 1. Factors and indicators determining a country's investment attractiveness.

Attractiveness Determinants Related to the Smartness Approach	Factors	Indicators	Source
Attractiveness in regard to the intelligence	Economic viability Current investment level Political stability Corruption level Trust in government Efficiency of government Market purchasing power	GDP per capita GDP per capita growth rate Investment share of GDP Return on equity Political stability/absence of violence/terrorism Corruption perceptions index Trust in Government index The shadow economy Government Effectiveness index Household income Household expenditure Average wages	Eurostat Eurostat Eurostat Eurostat The World Bank Transparency International The World Bank The Globaleconomy.com The World Bank Eurostat Eurostat Eurostat
Attractiveness in regard to networking and infrastructure	Renewable energy Logistic performance	Logistic performance index: Trade trans infrastructure Logistic performance index: Services Share of energy from renewable sources	The World Bank The World Bank Eurostat
Attractiveness in regard to sustainability	Environmental approach Human development level Social responsibility development level	Recycling rate of municipal waste Eco-innovation index Greenhouse gas emissions per capita Human development index Healthcare expenditure (% of GDP) Recorded offences by robbery per 100,000 population Fatal accidents at work per 100,000 persons employed In work at-risk-of-poverty rate	Eurostat Eurostat Eurostat United Nations development programme Eurostat Eurostat Eurostat Eurostat
Attractiveness in regard to digitalisation	Information communications and technologies (ICT) development	Level of internet access (households) Share of the ICT sector in GDP Use of computers and the internet by employees Mobile subscribers Digital single market—promoting e-commerce for businesses	Eurostat Eurostat Eurostat Eurostat Eurostat
Attractiveness in regard to learning	Education and science system development level Workforce qualifications Cost of workplace Workforce availability	Participation rate in education and training (last 4 weeks) Final consumption expenditure of households for education (% of total) Share of working age population Labour costs Labour force with intermediate education Individuals who have basic or above basic overall digital skills Unemployment rate Unemployment rate for young people	Eurostat OECD Eurostat Eurostat The World Bank Eurostat OECD OECD

		Export (% of GDP)	Eurostat
Attractiveness in regard to agility	Economic integrity with foreign markets	Export market shares—5 years % change	Eurostat
		Word Economic Forum The Travel and Tourism Competitiveness Index	WEF
	Tourist attractiveness	KOF Globalization Index	https://ethz.ch/en.html
	Globalisation	Rule of law index	World Justice Project
	Business complexity	Fiscal Freedom index	Heritage.com
	Rule of law performance	Self-employment rate	OECD
		Business freedom index	Heritage.com
	Self-employment level	Investment freedom index	Heritage.com
		Doing Business: starting a business	The World Bank
	Business freedom	Doing Business: enforcing contracts	The World Bank
	Market size	Shadow economy, percent of GDP	theglobaleconomy.com
		Net migration	The World Bank
		Share of urban population	Eurostat
Attractiveness in regard to innovation and being knowledge-driven	Functionality of the innovation system Cooperation between science, business, and government Business productivity level	R&D expenditures total % of GDP	Eurostat
		Business research and development expenditure (% of GDP)	Eurostat
		Government research and development expenditure (% of GDP)	The World Bank
		Automated teller machines (ATMs) per 100,000 adults	The World Bank
		Patent applications to the European patent office (EPO) by priority year	Eurostat
		Exports of high technology products as a share of total exports	Eurostat
		Labour productivity per person employed	Eurostat

Table 1 presents the concept of factors determining a country's investment attractiveness in regard to foreign direct investment, being a universal methodology, which may be used to analyse territories at different hierarchical levels. In the empirical analysis, 29 European countries from inside and outside the European Union were selected, which is why such an indicator as the availability of EU resources under the budget is not included in Table 1, unlike in Dorozynski and Kuna-Marszalek [56]. The assumption was made that the impact of the European Union and other countries' funding are incorporated in the whole result and process of economic development and separate determinants, in acceptance that the availability of subsidies and incentives from European Union resources significantly impacts the investment attractiveness of the countries [56].

We performed empirical research in the following sequence: (1) the clustering of countries and identification of the main factors responsible for the attractiveness of cluster countries; and (2) the prediction of foreign direct investment attracted to the country. We clustered countries hierarchically by self-organising neural networks (self-organising mapping method) using the Euclidean distance according to the logarithmic and main component values of all indicators (the explained dispersal is not less than 90%). We used two different methods for hierarchical classification in order to check whether it was expedient to develop all models incorporating all indicators or if it was enough to use the main components for quicker and simpler calculations.

For the time series prediction, these methods were used: recurrent neural networks (RNNs), long short-term memory (LSTM) neural networks, gated recurrent unit (GRU), and extreme learning machines (ELMs). We used multilayer artificial neural networks (Python programming language with Keras package; Keras package calculations were performed in TensorFlow package) for the identification of the most important factors determining investment attractiveness. We identified the indicators having the greatest impact on the result of prediction with sklearn.ensemble.ExtraTreesClassifier. Figure 1 presents a visualization of the methods used. In the use of RNN (see in Figure 1a), when moving from one part of the neural network to another, the

former value is retained, which is merged in the new part of the network with the newly received value. Then, the hyperbolic tangent function is utilized, and the output value is obtained, which is presented to the following part of the network. In the use of LSTM (see in Figure 1b), these neural networks also have a "chain" type structure, but their repeating unit has a completely different structure than simple recursive neural networks. Instead of a single layer, as in the case of RNN, the LSTM has as many as four layers with exceptional connectivity. In the use of GRU (see in Figure 1c), this network is similar to the LSTM-type network, as the LSTM uses various logical elements that control the presentation of information. One of the major differences between LSTM and GRU is that the GRU has no memory cells. In the use of ELM (see in Figure 1d), depending on the data and the task being solved, different extreme learning machines can be used with one layer, more layers, or hierarchical networks. The neurons in the hidden layer may not only be classical neurons, but basic functions may also be utilized, or these neurons may be generated from a subnetwork of neurons (e.g., the neuron is made up of a separate network).
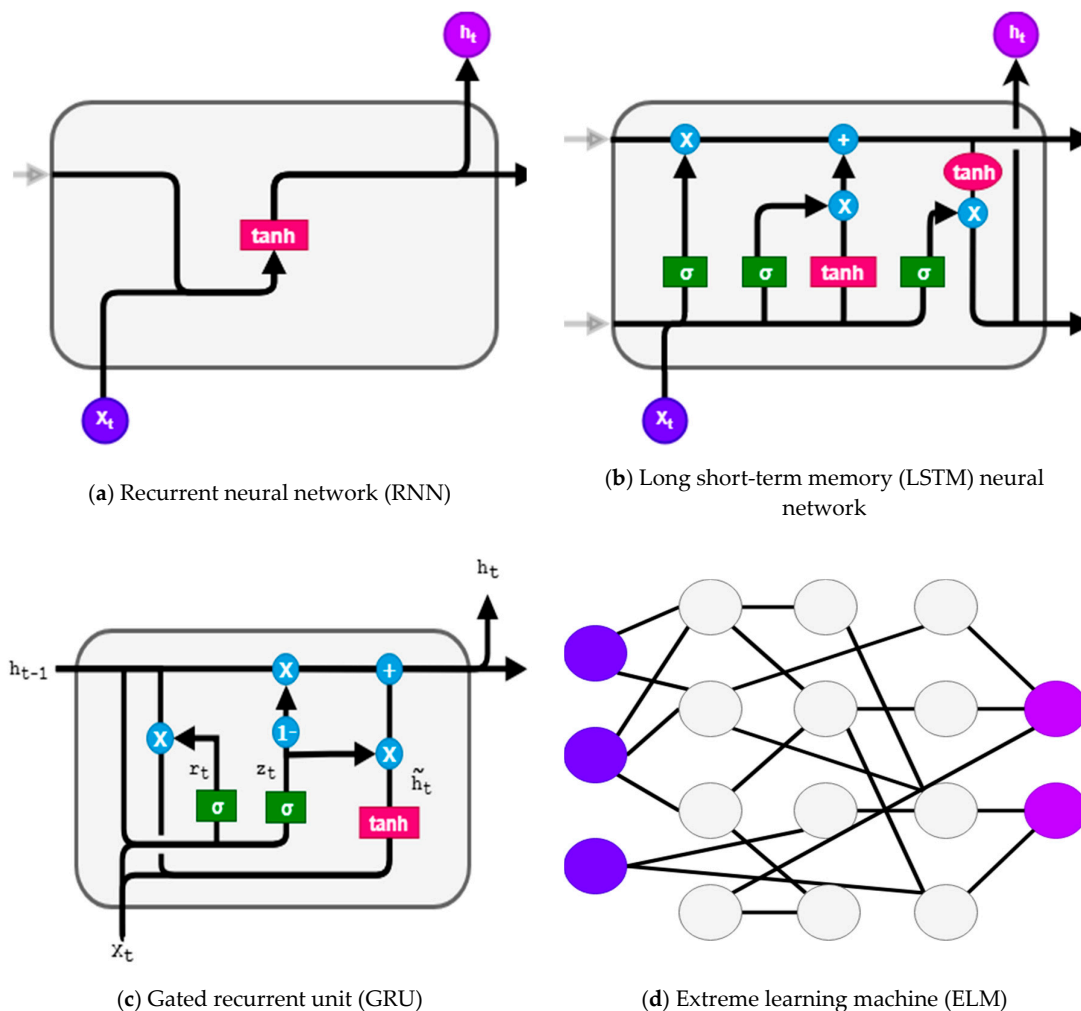

(**a**) Recurrent neural network (RNN)

(**b**) Long short-term memory (LSTM) neural network

(**c**) Gated recurrent unit (GRU)

(**d**) Extreme learning machine (ELM)

Figure 1. Visualization of used neural networks.

The empirical research developed more than 125,000 different RNNs, LSTMs, and GRUs and more than 22,000 ELM models of artificial neural networks by changing the different numbers of neurons in one, two, or three hidden layers and searching for the one with the lowest error for each country. The number of neurons used in hidden layers varied between 2 and 10 (step 1 was used). In the case of three-layer ELM models, we changed the number of neurons in the middle layer independently of the number of neurons in the first hidden layer. We employed different methods to evaluate the weight of the output layer in ELM models: least absolute shrinkage and selection

operator (LASSO), ridge regression, stepwise regression (step), and linear regression. We used different activation functions: logistic, hyperbolic tangent, and Gompertz. The research employed 2, 3, 5, or 10 independent components. We modelled time series data using models without external variables in order to evaluate whether or not external variables increased the accuracy of prediction models. Since the research study used short time series, we performed a crosscheck for future values. We used the beginning of the time series to train models and further values of the time series for checking. We compared different models using the mean absolute percentage error (MAPE) function.

We tested models for 10 d, using two computers optimising different models. To speed up the model-testing phase, use of a video card for calculations is recommended.

For empirical research, we used data from 2000–2018 from 29 European countries. The analysis included 58 indicators (see Table 1) and 31,958 observations of annual data for empirical research. The initial set of indicators was 74, but 16 indicators were excluded because of the high sparsity rate (high number of NA values) of variables. The initial set of countries was 32, but Serbia, Bosnia and Herzegovina, and Albania were excluded from the research because of insufficient data for indicator values. For neural network methods, it was best to use values from 0 to 1 because we used min–max normalization to complete this task. After these steps, data were ready for neural networks and models testing.

5. Results

We used self-organising neural networks to classify countries under attractive groups in regard to foreign direct investment. By using two variations of self-organizing mapping (self-organizing neural networks) clustering, including all variables and main components, we classified European countries under six clusters (we assumed six clusters based on clustering metrics with the elbow method), i.e., different regions in regard to investment attractiveness (see Figure 2), and we identified the main factors determining the investment attractiveness of individual groups of countries (see Table 2). Both clustering cases produced the same results and, therefore, were suitable for solving the tasks of factors determining the clustering of countries according to investment attractiveness; however, notwithstanding a more complicated and longer calculation, for classification we recommend using all values (not of the main components) due to a simpler interpretation of results in economic tasks.

Figure 2. Map of hierarchical clustering results by using all indicators.

Table 2. Countries of hierarchical clustering and the key factors determining foreign direct investment.

Cluster No	Countries	Geographical Location	Key Factors Determining a Country's Investment Attractiveness
1. Red	Croatia, Bulgaria, Romania	Southeastern European countries	Economic viability, Economic integrity with foreign markets, Market size, Corruption level, Political stability, Information communications and technologies (ICT) development, Workforce qualifications, Business productivity level, Globalisation, Cost of workplace, Current investment level, Trust in government, Education and science system development level
2. Blue	Italy, Spain, Portugal	Southern European countries	Economic viability, Workforce availability, Workforce qualifications, Business productivity level, Market purchasing power, Business complexity, Tourist attractiveness
3. Green	Lithuania, Latvia, Estonia, Hungary, Poland, Slovenia, Slovakia, Czech Republic	Eastern and Central European countries	Economic viability, Human development level, Economic integrity with foreign markets, Market size, Workforce qualifications, Corruption level, Political stability, ICT development, Workforce qualifications, Functionality of the innovation system, Business productivity level, Cooperation between science, business and government, Business complexity, Human development level, Trust in government, Efficiency of government, Education and science development level, Renewable energy
4. Violet	United Kingdom, Germany, France	Western European countries	Market size, Workforce qualifications, Globalisation, Business complexity, Business freedom, Market purchasing power, Business complexity, Business productivity level, Tourist attractiveness, Logistic performance, Trust in government, Government efficiency, Rule of law performance, Social responsibility development level
5. Orange	Iceland, Norway, Finland, Denmark, Switzerland	Northern European countries and Switzerland	Economic viability, Human development level, Economic integrity with foreign markets, Market size, Corruption level, Functionality of the innovation system, Cooperation between science, business and government, Workforce qualifications, Business productivity level, Environmental approach, ICT development, Globalisation, Workplace price, Market purchasing power, Existing investment level, Human development level, Trust in government, Government efficiency, Logistic performance, Rule of law performance, Social responsibility development level, Renewable energy
6. Yellow	Belgium, Austria, the Netherlands, Ireland, Luxembourg, Malta	Other countries not associated by geographical criterion	Market size, Workforce availability, Workforce qualifications, Business productivity level, ICT development, Workplace price, Business complexity, Tourist attractiveness, Logistic performance

We identified the key factors determining a country's investment attractiveness recommended in making and substantiating strategic decisions on investment environment improvements and in developing new prediction models for foreign direct investment. A country's investment attractiveness was impacted by the factor of the country's geographical space that was not included in the set of assessment indicators as an individual characteristic (see Table 2). The clustering of countries highlighted the geographical fact of the presence of neighboring countries (except several

countries in cluster 6). In addition, the investment attractiveness of geographically similar countries depends on similar factors.

We obtained the most accurate results of foreign direct investment prediction from ELM models while using the main or independent components (see Appendix A, Table 3, and Table 4), including recurrent, long short-term memory, gated recurrent unit neural network, and extreme learning machine methods. The analysis confirmed that the proposed methods were suitable to predict foreign direct investment, as they managed to record data from the past and incorporate them in prediction. In nearly all cases, artificial neural network prediction models provided more accurate prediction results compared with the linear regression and naive models. We observed an exceptional case in the prediction of Italy's foreign direct investment, as the naive model forecasted Italy's foreign direct investment best.

To forecast the 2018 foreign direct investment, we used the artificial neural network models providing the most accurate FDI predictions (see Table 3).

Table 3. Forecast of foreign direct investment (FDI) trends.

Country	Forecast 2018 Foreign direct investment (FDI) (billion EUR)	Actual 2018 FDI (billion EUR)	2017 FDI (billion EUR)	2018–2017 Change in FDI (%)	Coincidence of Actual and Forecast FDI
Austria	10.34	11.25	15.61	−51%	+
Belgium	−17.10	−64.05	−39.48	131%	+
Bulgaria	2.41	2.57	2.18	10%	+
Switzerland	29.97	−67.68	37.86	−26%	−
Czech Republic	3.88	8.49	9.21	−137%	+
Germany	51.86	105.28	77.98	−50%	+
Denmark	1.20	5.39	2.36	-97%	+
Estonia	1.47	1.03	1.56	−6%	+
Spain	27.79	45.40	6.2	78%	+
Finland	13.70	−5.50	14.2	−4%	−
France	43.39	66.82	47.34	−9%	+
Croatia	0.97	1.28	2.04	−110%	+
Hungary	15.10	−75.18	−13.48	189%	−
Ireland	−5.63	21.36	−3.44	−39%	−
Iceland	−1.84	−0.49	−7.02	282%	+
Italy	15.03	30.90	9.24	39%	+
Lithuania	1.25	0.87	1.19	5%	+
Luxembourg	21.98	N/A	6.62	70%	N/A
Latvia	0.86	-	1.14	−33%	N/A
Malta	3.54	4.75	3.46	2%	+
Netherlands	317.11	−163.16	316.54	0%	+
Norway	2.15	−19.94	1.64	24%	−
Poland	12.17	11.32	10.67	12%	+
Portugal	12.71	4.86	10.02	21%	+
Romania	7.15	6.88	5.95	17%	+
Sweden	12.16	5.82	31.53	−159%	+
Slovenia	1.15	1.51	1.08	6%	+
Slovakia	3.40	-	5.92	−74%	N/A
United Kingdom	31.86	58.65	64.69	−103%	+

The forecast showed an increase in foreign direct investment in 16 out of 29 countries concerned (55%), compared with 2017. The comparison of the forecast and actual values has shown that they were not always close. In many cases, prediction by artificial neural networks allowed us to predict accurately the trend itself but not the value. The most accurate prediction was for countries in Central

and Eastern European clusters. Time series forecasts using annual indicators are relatively small; therefore, in the event of big jumps, mathematical methods do not always allow this to be recorded and used in subsequent forecasting. In addition, research may involve more binary variables, such as the start of Brexit agreements and economic crisis assessment indexes. To achieve more accurate forecasts using mathematical models, these methods can be applied by training artificial neural networks for the whole set of countries, rather than for each country individually, and then using the developed model to forecast foreign direct investment in an individual country. Such use of artificial neural networks would result in a larger sample of training; therefore, artificial neural networks could accurately record relationships among individual indicators, but these artificial neural networks would require much more historical data and longer training. Larger samples will require more learning time and will not allow instant results to be received (computing process will extend the time-consuming grid [87]), which remains as a difficult challenge in research performance. The use of more complex and deeper structure models with bigger data samples requires computing power, which reflects the timing problems, as it is not an estimation problem but a technological problem [88].

6. Discussion and Research Limitations

The increasing possibilities of using artificial intelligence in different kinds of research and a rapidly growing use of artificial intelligence [89,90] leave no doubts as to the potential of this topic and great prospects for it in the near future. Despite the fact that artificial intelligence (more specifically, one of its branches, i.e., machine learning) is less common in economic modelling than linear regression models because of complicated algorithms, it is easy to predict that the situation will change soon, and the use of artificial intelligence in economic modelling is the issue of today, not of the future.

The empirical analysis let us identify such advantages of the use of artificial intelligence in countries' investment attractiveness:

- A faster and more accurate answer, compared with the currently used methods like manual index calculation. The artificial intelligence methods do not necessarily require human intervention for collection of data (based on the methodology framework); also, identification of factor significance based on the template of previous years.
- A suitable and more accurate method for analysing and characterizing multicriteria concepts, as the artificial intelligence can handle very large quantities of indicators;
- Possibilities of predicting and modelling values of indicators;
- Possibilities of analysing each country individually in the context of influence of other countries;
- Possibilities of grouping countries according to socio-economic advantages, identifying the main competitor countries.

The empirical analysis let us identify such limitations of the use of artificial intelligence in countries' investment attractiveness:

- Lack of data. Since any method of artificial intelligence is data-intensive, data availability, and particularly the availability of up-to-date data, becomes an extremely important factor. Compared with other statistical techniques, neural networks require the data to split into train, test, and validate sets. Because of this, a much bigger sample size is needed compared with other techniques.
- Machine learning with a teacher requires the prior assignment of training data to classes, which requires expert judgement (the expert must assign the observations in question to a certain class). Incorrect expert judgements may lead to an incorrect model development process and misuse of these models and inappropriate conclusions.
- The principle of "black box". In the case of neural networks, many different calculations, interaction assessments, and so on take place in the "black box", but the final result does not explain how the model used data and how everything worked inside the algorithm.
- Methods of artificial intelligence use a significant quantity of computer resources; thus, these methods are not always usable, and the methods are time consuming and last for a long time.

The advantages and limitations of the use of artificial intelligence in the assessment of countries' investment attractiveness proved the need for soft competences for work with artificial intelligence. Economic analysis often addresses a dichotomous question when the answer provided by artificial intelligence is not always sufficient. The competences of the user of the results and the interpreter of the findings of economic analysis play a crucial role. The management and use of artificial intelligence in decision-making requires professional and technological knowledge [91] and emotional intelligence [25,29]. Every human being, when the most appropriate situation occurs for him, can disclose his talent(s) to be smart [71,92,93]. The empirical analysis let us identify the soft competences under the smartness approach, which are required for the work with artificial intelligence (see Table 4). A smart human being is not an absolute given. Smartness becomes evident in the relationship of a human being with the physical and socio-cultural environment and their actions [94].

Table 4. The competences needed for the work with artificial intelligence in economic analysis.

Competences	Features of the Competence	Areas for the Use of Competence
Creativity	This competence helps to see the socio-economic system differently, but at the same time accurately [24], to create unique strategies for achieving ambitious developmental goals and socio-economic system to be effective.	It is in particular necessary at the stages of perceiving the concept in question, developing a methodological model, and selecting economic modelling scenarios; economic impact analysis; interpretation of research results and policy recommendations.
Intelligence	This competence helps to assess adequately processes and trends in the external environment of the object/concept analysed.	It is particularly necessary in the creation of a methodological model; interpretation of research results (clustering and investment attractiveness determinants; forecast results); limitations and bottleneck of future research.
Agility	This competence helps to quickly foresee new changes or needs and make decisions and respond to new opportunities and threats in a timely manner.	It is particularly necessary at the stages of perceiving the concept addressed and policy recommendations.
Networked	This competence helps to create co-operative community culture by obtaining information and various resources, maintaining relations with other participants in the process, and sharing research results.	It is particularly necessary at the stages of perceiving the concept, economic impact, and policy recommendations.
Sustainability	This competence helps to reconcile environmental, economic, and socio-cultural determinants without posing a threat to the future.	It is particularly necessary at the stages of perceiving the concept, creating a methodological model, economic impact, and policy recommendations.
Social responsibility	This competence helps to identify and expand the connections between societal and economic progress employing the philosophy of shared value creation [94].	It is particularly necessary at the stages of perceiving the concept addressed, developing a methodological model, and policy recommendations.
Innovativeness	This competence helps to identify and use new and effective approaches and techniques in the process of economic development analysis.	It is particularly necessary at the stages of perceiving the concept, creating a methodological model, selecting scenarios for economic modelling, and policy recommendations.
Digitality	This competence helps to make the economic development analysis process effective, more accurate, and quicker.	It is particularly necessary at the stages of selecting scenarios for economic modelling and policy recommendations.
Learning	This competence helps to ensure continuous improvement of the process and results of economic development analysis by accumulating information, knowledge and experience, and being able to use them.	It is particularly necessary for the development of a methodological model, impact analysis, interpretation of research results, and policy recommendations.

Curiosity and knowledge-driven	This competence helps to ground economic development analysis on scientific knowledge and re-think best practices.	It is particularly necessary at the stages of perceiving the concept, creating a methodological model, selecting scenarios for economic modelling, economic impact analysis, and policy recommendations.

When working together with artificial intelligence, such a person will be able to analyse smartly adaptive, complex socio-economic systems, address dichotomous questions, and replace the holistic approach with the reductionist approach in policy- and decision-making.

7. Conclusions and Further Research

This paper contributes to economic development literature by clarifying the interactions between the concept of countries' investment attractiveness and smartness approach. The analysis of the concept of countries' investment attractiveness by employing dynamic capacities of a country's economic subjects and conditions for enabling them within smartness approach reveals new aspects of this concept and meets the criteria of timeliness and modernity. The findings are important for fostering a smartness approach in economic development.

The concept of investment attractiveness is characterized as unrestricted in the spatial approach. The limitation of this concept to different hierarchical levels of territories is inhered by the availability of characterizing statistical indicators. A country's investment attractiveness is defined as the ability of its economic subjects through its competences (intelligence, sustainability, digitization, agility, innovativeness, networking, knowledge, and learning) and the country's environment to attract and maintain the investments to the country.

The presented framework of the analysis of countries' investment attractiveness in the smartness approach is a universal methodology, which may be used to analyse territories at different hierarchical levels. Important implications of the presented framework for decision-makers is that application of the presented framework allows, in compliance with modern economy tendencies, to perform empirical research, which provides results of a country's investment attractiveness at a fixed point in time and dynamically, and in relation to other countries, identification of factors which increase or decrease investment attractiveness.

The use of artificial intelligence in the analysis of investment attractiveness allows a faster and more accurate answer to be obtained; allows a more detailed characterization of the concept, as it can handle very large quantities of indicators; allows predicting and modelling values of indicators; allows each country to be analysed individually in the context of the impacts of other countries; and allows countries to be grouped according to socio-economic and spatial similarities. The limitations of the use of artificial intelligence in countries' investment attractiveness are the lack of data, the principle of "black box", and the use of a significant quantity of computer resources.

Work with artificial intelligence also requires professional and technological knowledge and emotional intelligence. The empirical analysis let us identify the needed soft competences through the smartness approach: creativity, intelligence, agility, networked, sustainability, social responsibility, innovativeness, digitality, learning, curiosity and being knowledge-driven. All these competences together are mostly used in all stages of economic analysis.

There are a number of future research opportunities, as this is still a novel research area in the field of economic development. It would be worthwhile to carry out further in-depth research into the level of readiness of a country's authorities to use artificial intelligence, to identify the requisite collective competences of using artificial intelligence in economic analysis, and to enhance the accuracy of forecasting foreign direct investment by incorporating binary variables and updating the methodological model.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Characteristics of the best models of each country used in the research, based on MAPE.

Country	Method	Structure	Dimension reduction (DM) method	Number of DMs	Root-mean-square error (RMSE)	Normalized root-mean-square error (NRMSE)	Mean absolute error (MAE)	Mean percentage error (MPE)	Mean absolute percentage error (MAPE)	Mean absolute scaled error (MASE)
Austria	GRU	10	Principal components analysis (PCA)	6	459.77	140.60	383.04	60.75	67.16	0.67
Belgium	ELM	9; 2; 9	Linear model (lm)	-	15.57	50.10	11.64	26.15	40.07	0.43
Bulgaria	ELM	8; 3; 8	step	-	0.37	65.40	0.31	−8.80	18.22	0.34
Switzerland	ELM	4; 7; 4	lasso	-	44.04	85.00	30.47	59.78	63.63	0.47
Czech Republic	ELM	9; 8; 9	step	-	2.12	60.70	1.39	5.98	15.10	0.30
Germany	ELM	6; 4; 6	lm	-	10.06	52.10	6.79	−6.61	12.39	0.31
Denmark	ELM	7; 2; 7	lm	-	6.73	69.70	4.72	64.05	64.05	0.56
Estonia	GRU	4	Independent component analysis (ICA)	2	0.71	47.60	0.52	10.11	17.04	0.38
Spain	ELM	3; 5; 3	lm	-	5.57	49.10	4.68	−13.67	15.42	0.27
Finland	GRU	8/8/8	PCA	6	163.77	258.80	154.33	85.74	85.74	1.93
France	ELM	7; 3; 7	lm	-	6.23	39.80	4.91	−21.64	21.64	0.29
Croatia	GRU	9	ICA	2	2.26	109.90	1.45	17.09	17.23	0.60
Hungary	ELM	5; 2; 5	step	-	20.28	66.60	13.94	−40.97	66.35	0.45
Ireland	ELM	9; 7; 9	lasso	-	37.69	47.80	22.60	3.65	19.39	0.26
Italy	ELM	8; 6; 8	lm	-	5.22	63.90	4.14	−46.98	59.47	0.52
Lithuania	GRU	8/8/8	ICA	2	0.09	15.70	0.08	−7.95	9.98	0.08
Luxembourg	ELM	2; 9; 2	step	-	10.94	20.10	7.15	−10.09	30.78	0.17
Latvia	ELM	10/10/10	step	-	0.11	33.80	0.09	−7.56	10.09	0.41
Netherlands	ELM	4; 4	step	-	74.02	90.80	59.15	−27.53	30.35	0.62
Norway	ELM	6; 2; 6	step	-	13.26	80.10	9.71	−38.33	68.98	0.63

Poland	ELM	2; 5; 2	lm	-	2.51	31.40	2.01	−2.47	16.55	0.24
Portugal	ELM	10/10/10	step	-	6.73	95.60	4.24	1.27	37.06	0.54
Romania	ELM	4; 2; 4	step	-	0.82	68.10	0.49	−7.90	9.32	0.61
Sweden	ELM	4; 4	step	-	4.52	64.60	3.22	−0.74	49.50	0.42
Slovenia	GRU	4	ICA	10	1.15	81.00	0.60	12.46	17.97	0.28
Slovakia	RNN	10/10/10	PCA	6	14.06	133.10	10.70	47.55	47.55	0.57
United Kingdom	ELM	9/9/9	lm	-	32.12	33.40	16.45	6.05	9.80	0.27
Malta	RNN	3/3/3	PCA	7	118.91	90.50	62.69	36.40	36.40	0.59
Iceland	RNN	3	No	-	0.99	23.80	0.87	11.13	19.61	0.25

Table A2. Comparison of the best artificial neural network prediction models with the linear regression and naive models, based on MAPE.

Country	Models of Artificial Neural Networks						Linear Regression Models	Naive Models
	Method	Structure	DM	Number of DMs	Activation function	MAPE	MAPE	MAPE
Austria	GRU	10	PCA	6	Tanh	67.16	1267.71	331.88
Belgium	ELM	9; 2; 9	lm	-	-	40.07	274.31	74.53
Bulgaria	ELM	8; 3; 8	step	-	-	18.22	397.11	54.54
Switzerland	ELM	4; 7; 4	lasso	-	-	63.63	124.77	163.10
Czech Republic	ELM	9; 8; 9	step	-	-	15.10	149.46	124.34
Germany	ELM	6; 4; 6	lm	-	-	12.39	104.54	78.48
Denmark	ELM	7; 2; 7	lm	-	-	64.05	345.57	731.38
Estonia	GRU	4	ICA	2	Gompertz	17.04	166.91	156.79
Spain	ELM	3; 5; 3	lm	-	-	15.42	123.59	44.03
Finland	GRU	8/8/8	PCA	6	Tanh	85.74	217.51	151.26
France	ELM	7; 3; 7	lm	-	-	21.64	155.54	135.02
Croatia	GRU	9	ICA	2	Gompertz	17.23	822.38	649.76
Hungary	ELM	5; 2; 5	step	-	-	66.35	346.78	238.11
Ireland	ELM	9; 7; 9	lasso	-	-	19.39	105.28	80.22
Italy	ELM	8; 6; 8	lm	-	-	59.47	260.67	43.71
Lithuania	GRU	8/8/8	ICA	2	Gompertz	9.98	83.56	27.45
Luxembourg	ELM	2; 9; 2	step	-	-	30.78	333.11	204.62
Latvia	ELM	10/10/10	step	-	-	10.09	246.51	69.08
Netherlands	ELM	4; 4	step	-	-	30.35	250.56	63.35
Norway	ELM	6; 2; 6	step	-	-	68.98	569.19	604.09

Country	Models of Artificial Neural Networks						Linear Regression Models	Naive Models
	Method	Structure	DM	Number of DMs	Activation function	MAPE	MAPE	MAPE
Poland	ELM	2; 5; 2	lm	-	-	16.55	62.12	241.27
Portugal	ELM	10/10/10	step	-	-	37.06	173.69	155.12
Romania	ELM	4; 2; 4	step	-	-	9.32	70.42	15.65
Sweden	ELM	4; 4	step	-	-	49.50	591.38	136.97
Slovenia	GRU	4	ICA	10	Logistic	17.97	126.72	55.14
Slovakia	RNN	10/10/10	PCA	6	Tanh	47.55	149.13	161.85
United Kingdom	ELM	9/9/9	lm	-	-	9.80	157.28	33.63
Malta	RNN	3/3/3	PCA	7	Tanh	36.40	1687.81	226.21
Iceland	RNN	3	-	-	Gompertz	19.61	200.26	99.13

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