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Functionality between the size and indicators of smart cities: A research challenge with policy implications

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ABSTRACT

The paper focusses on the concept of a smart city and its specific components in relation to size of the city. Smart cities are a topic whose key importance is being increasingly recognised across both academic disciplines and urban planning. The idea of a smart city is a dream of urban planners all over the world, and a subject of many research and business initiatives as well as policy debates. As cities vary considerably in size, it is important to ask if the size influences the level of selected indicators of smart cities. Our main presumption is that the development level of indicators of smart cities varies in cities of different size. Our scientific objective is to find a simple understandable model linking the categorical variable "city size" to a group of smart city indicators. Our data set contains 26 smart city indicators for 158 European smart cities, divided into two sizes: medium-sized cities and larger cities. We draw from the methodology of "European Smart Cities" elaborated by the Vienna University of Technology (Project ID: 314704) that classify European smart cities and smart city indicators by considering their size.

Analysing the statistics by using decision tree modelling, we identify the most significant indicators of smart cities that can divide smart cities into size categories with impressive 96.2% correct classification. Besides excellent classification result based on real empirical data, several research results overturn common assumptions about smart cities.

Based on the research results the paper also highlights intriguing future challenges in smart city research and policy development. Several research results have policy implications and might be useful for urban planners, policy representatives and decision makers.

1. Introduction

Cities and urban agglomerations are a great phenomenon of the past, present and future. There are tons of materials, studies, books and articles related with cities in terms of urban economics and development (inter alia Capello & Nijkamp, 2004, McCann, 2001, O'Sullivan, 2003 etc.) and agglomeration economics (for more information see for example Glaeser, 2010). We will focus on those that fit to our purpose, in particular to smart cities.

The concept of smart cities is currently a very popular and fashionable approach to urban development. Nowadays, almost all cities claim to be more or less smart. Their focus seems to be on the role of Information and Communication Technology (ICT) infrastructure, although much research has also been carried out on the role of human capital, social and relational capital and environmental interest as important drivers of urban growth (Caragliu, Del Bo, & Nijkamp, 2014; Hollands, 2008). The development of a smart city approach and its implementation in various countries has generated impressive research results and policy challenges.

Transforming a city into a smart city requires substantial effort from its political representatives, administrators, inhabitants, entrepreneurs, as well as from its various communities. Smart city concept is rapidly gaining momentum and worldwide attention as a promising response to the challenge of urban sustainability in both large and small towns (Bibri & Krogstie, 2017; Caragliu, Del Bo, & Nijkamp, 2011).

The size of a city is considered as an important driver of economic development. Empirical evidence from the US and the UK shows that large cities lead to greater productivity and economic growth through the generation of agglomeration economies which allow for a more productive use of available resources (Frick & Rodríguez-Pose, 2017; Melo, Graham, & Noland, 2009; Rosenthal & Strange, 2004). At the same time, many researchers and policy makers have voiced concerns about negative consequences of high level of urbanization on social (i.e. increased urban congestion), environmental (i.e. increased pollution)

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and economic (i.e. rising interpersonal and interspatial inequality) performance of large cities (Frick & Rodríguez-Pose, 2016). Large cities tend to be associated with diversity and a high concentration of the creative classes. Florida (2005) claims that more densely populated cities with high concentration of creative class are noted for their innovative spirit. In contrast, small and medium sized cities tend to be thought of as places with a healthier environment and a higher ecological awareness.

Despite the enormous interest in the area of smart cities, it is not clear from research neither from the practice the impact of a city's size on the “smartness” of the city. Besides ‘European Smart City’ approach, theoretical and empirical studies on smart cities are overlooking the city size dimension. Therefore, this paper focuses on identifying indicators that allow us to correctly predict the size and the character of European smart cities.

The remainder of the paper is structured as follows: the next section describes the theoretical and empirical literature that explores the link between smart cities and size of the city. Main components of smart cities, namely human factor and ICT in the role of crucial components of modern urban development, are discussed in relation to city size. The third section addresses our methodology; used indicators and presents the dataset. The results are included in the fourth section and discussed in the section five. The final part concludes main findings and proposes areas for further research and highlights policy challenges.

2. Literature review

The smart city concept, after its first appearance in 1998 (Mahizhnan, 1999; Van Bastelaer, 1998), has undergone many changes as a component of several concepts reflecting various ways of understanding smartness in urban development. According to Anttiroiko (2015) smartness can be seen both in the design of policy and its implementation. Increasing smartness would then revitalize local economies to meet the challenge of a constantly evolving local-global dialectic. To gain a relatively strong socio-economic position in an open spatial system, cities or regions have to be able to exploit their indigenous assets such as knowledge, technology, entrepreneurship, accessibility, sustainability and culture (Caragliu et al., 2011; Kourtit & Nijkamp, 2013), represented by the approach of smart cities. According to Giffinger, a smart city is a well performing city built on the “smart” combination of endowments and activities of self-decisive, independent and aware citizens (Giffinger, Fertner, Kramar Meijers, & Pichler-Milanovic, 2007). The word “smart” includes various features as technological and inter-connected, but also sustainable, comfortable, attractive, safe (Sansaverino, Sansaverino, Vaccaro, & Zizzo, 2014). According to Caragliu et al. (2011) city tends to be smart when investments in human and social capital and traditional (transport) and modern (ICT) infrastructure fuel sustainable economic growth and a high quality of life, with a wise management of natural resources, through participatory governance. Smart cities represent a conceptual urban development model based on the utilization of human, collective, and technological capital for the enhancement of development and prosperity in urban agglomerations“(Angelidou, 2014, p.3). Abella, Ortiz-de-Urbina-Criado, and De-Pablos-Heredero (2017) identifies smart city as a public-private ecosystem providing services to citizens and their organizations with strong support from technology, and considers the social and economic impact on the society. The message from practice is that the smart city is essentially a group of projects, initiatives and actions, carried out both by public and by private organizations. Because this group results from the spontaneous choices of a range of self-interested actors, but acts on the specificity of a city, the results are very heterogeneous. To design a definition based on one case study is to write a definition describing a specific smart city, and not a standard (Hollands, 2008).

Despite the big interest in this phenomenon, generally accepted definition of smart city still lacks (Anthopoulos & Fitsilis, 2013; Dameri, 2017) and there is a disagreement between academics and practitioners about the main component of a smart city. In the academic debate, it is an intellectual capital (people, citizens or community). In the empirical vision expressed mainly by large companies, the main component is ICT (Sansaverino et al., 2014).

Therefore, the construct of smart cities has emerged as a strategic agenda over the past years, emphasis the increasing importance of ICT for encompassing modern urban development factors in a common framework and for profiling cities' competitiveness based on their social and environmental capital (Caragliu & Nijkamp, 2009; Paskaleva, 2014). The availability and quality of the ICT infrastructure is not the only definition of a smart or intelligent city. In contrast to this predominantly technical approach to smart cities, other definitions stress the role of human capital and education in urban development. Berry and Glaeser (2005) and Glaeser and Berry (2006) show, for example, that the most rapid urban growth rates have been achieved in cities where a high share of educated labour force is available. Shapiro (2006) and Hollands (2008) come to joint conclusion that smarter cities start from the human capital side, rather than blindly believing that ICT can automatically create a smart city. Factors like the capacity of human (Berry & Glaeser, 2005; Glaeser & Berry, 2006) and the role of higher education, skills, creativity and talent (Shapiro, 2006; Winters, 2011) have all emerged as the main drivers of smart urban development. According to European Parliament (2014), a smart city consists of not only components but also people. Securing the participation of citizens and relevant stakeholders in the smart city is therefore another success factor. As noticed by Russo, Rindone, and Panuccio (2016), this definition explicitly introduces people component in the system concept of smart cities.

Besides a fairly wide-range debate on the crucial component of smart city, there is almost no debate in scientific literature discussing the relation between the size of the city and crucial components of urban development. Since the beginning of the 21st Century, the same as in past (inter alia Glaeser, 2011), mega cities and metropolitan regions get particular attention among politicians, city planners and managers and the international media. Research results (Duranton, 2015; McCann, 2016; McCann & Acs, 2011; OECD, 2014) showed the importance of metropolitan areas from the productivity point of view, but also revealed serious concerns related with environmental sustainability, pollution, traffic problems or quality of housing. Several other studies (Cox & Longlands, 2016; ESPON, 2006; Giffinger et al., 2007) uncovered that small and medium-sized cities play a more significant role in the economy, than policymakers acknowledge. According to Kumar and Dahiya (2016) wealth of cities depends on their population size and other factors. Statistics show that the city size matters a great deal in GDP generation of a city in a country (OECD, 2014).

In Europe, 67% of urban inhabitants live in medium-sized cities (i.e. smaller than 500,000 inhabitants), while just 9.6% are located in cities having more than five million inhabitants. Europe is also characterised by a more polycentric and less concentrated urban structure compared to, for instance, the USA, India or China.[1] Several EU member states has only one metropolitan city, usually the capital (for example Hungary, Latvia, Lithuania or Slovakia) and several member states have no single city bigger that 500,000 inhabitants (for example Estonia or Slovenia). Thus, there is a strong indication that population size of city matters, especially in EU member states, concerning its urban economy and smart city development (Kumar & Dahiya, 2016). In the current climate of metropolitan fever, areas in the shadow of metropolitan regions tend to be neglected. They seem to be the negligible victims of mainstream policies in times of globalisation and regional competition (ESPON,

[1] (There are 23 cities of > 1 million inhabitants and 345 cities of > 100,000 inhabitants in the European Union, representing around 143 million people. Only 7% of the EU population live in cities of over 5 million inhabitants compared to 25% in the USA.) (Cities of Tomorrow 2011)

Table 1
Smart city characteristics and their indicators.

Smart economy	Smart people	Smart governance	Smart mobility	Smart environment	Smart living
(Competitiveness)	(Social and human capital)	(Participation)	(Transport and ICT)	(Natural resources)	(Quality of life)
Innovative spirit	Level of qualification/education	Participation in public life/political awareness	Local accessibility/local transport system	Environmental conditions (only for MSC)	Cultural facilities
Entrepreneurship	Lifelong learning	Public and social services			Health conditions
Economic image and trademarks/city image	Ethnic diversity	Transparent governance/Efficient and transparent administration	(Inter)-national accessibility	Air quality (no pollution)	Individual security
Productivity	Open-mindedness		Availability of ICT-infrastructure/ICT infrastructure	Ecological awareness	Housing quality
Flexibility of labour market/labour market			Sustainability of transport system	Sustainable resource management	Education facilities
International embeddedness/International integration					Touristic attractiveness
					Economic welfare/Social cohesion

Source: Giffinger et al., 2007, p. 12.

2006). Although there are some harbingers of change, there is still need for serious scientific research to improve the practical implementation of this concept for cities of all sizes. It is crucial to pay attention on a city size not only from the scientific point of view, but also from management point of view in terms of planning and decision-making.

3. Methodology and data

In the following sections, we empirically test the relationship between city size and indicators of smart cities. The scientific objective of our paper is to find a simple understandable model linking the categorical variable “city size” to a group of smart city indicators with a certain value. The research question we wish to answer is whether we can identify the crucial smart city indicator(s) and their level of development (value) that accurately classify smart cities according to their size.

To serve this purpose, we employ robust methodology, comprising several scientific and statistical methods divided into three main steps. Firstly, we used statistical parameters (arithmetic mean, median and standard deviation) and Wilcoxon test in order to summary and sort out smart cities indicators for both city size groups. Secondly, we used standard multivariate classification, namely discriminant analysis and logistic regression in order to find classification of size city groups by suitable multivariate statistical model. As they have only a limited ability to distinguish between different size of city and smart cities indicators, we choose the decision tree as a main methodological instrument in our paper (see Tables 3,4,5 and 6). The decision tree or classification and regression tree creates a classification model that classifies values of the output variable based on the values of input (predictor) variables (for more information see Biggs, de Ville, & Suen, 1991, Bramer, 2016, Breiman, Friedman, Stone, & Olshen, 1984, Goodman, 1979, Lin, Noe, & He, 2006, Loh, 2008, Rokach & Maimon, 2015). The method builds decision trees for predicting dependent categorical variable (in our case it is size of the city) by continuous or categorical independent variables (smart city indicators). Further we use abbreviation of original term Classification and regression tree (CRT) proposed by Breiman or term “decision tree.” CRT separates the data into segments that are as homogeneous as possible with respect to the dependent variable. A terminal node in which all cases have the same value for the dependent variable is a homogeneous “pure” node (Breiman et al., 1984). CRT is simple to understand, interpret, and at the same time able to handle both numerical and categorical data from many variables. In our case data set contains 158 cities with 27 indicators. Besides, CRT allows validating a model using by statistical tests so we can account for the reliability of the model (Gareth, Witten, Hastie, & Tibshirani, 2015). For creating decision trees, we employ the statistical system IBM SPSS version 19 (*IBM SPSS Decision Trees* 19, 2010) and edit smart cities indicators data set.

As it was briefly mentioned in the introductory part of the paper, ‘European Smart Cities’ approach considered size of the city in its methodology that was elaborated by the Vienna University of Technology (Centre of Regional Science). In 2007 it was revised for the specific requirements of the PLEEC project financed by 7th Framework Programme, aimed at evaluating and benchmarking smart or potentially smart city profiles. More information is available at www.smart-cities.eu. Based on their extensive research, we created extensive data set of 77 medium-sized and 81 larger cities in the European Union to test the validity of the common stereotypes associated with the smart cities of different size.

In the literature can be found a few smart city rankings or different urban indicators (e. g. The Smart Cities Wheel, Bilbao Smart City Study, Smart City PROFILES, City Protocol etc.) (Ahvenniemi, Huoila, Pinto-Seppä, & Airaksinen, 2017; Klopp & Petretta, 2017). As the most suitable approach for our research we consider European Smart Cities Ranking (Giffinger et al., 2007), due to its implementation in conditions of European cities and provisioning a comprehensive list of indicators covering wide range of smart city characteristics (see Table 1).

The European (EU 27 + Norway and Switzerland) cities to be investigated are divided into two categories – medium-sized cities (MSC) and larger cities (LC). Due to a lack of data and various administrative boundaries, the initial list of 1600 smart, or potentially smart cities across 29 countries, was reduced to 158 cities from 25 countries, namely Austria, Belgium, Bulgaria, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Netherlands, Poland, Portugal, Romania, Spain, Slovakia, Slovenia, Sweden, United Kingdom. 77 medium-sized smart, or potentially smart, cities were chosen if they satisfied three criteria: they had a population between 100,000 and 500,000, at least one university, and a catchment area with < 1,500,000 inhabitants. 90 larger smart, or potentially smart, cities were selected after fulfilment of three criteria: population between 300,000 and one million (this is Urban Audit's definition of a core city); listed in the Urban Audit database; data covering > 80% of the indicators we wished to analyse (Giffinger et al., 2007). As several cities in our data set appeared in both size categories, (altogether nine cities), we have assigned them only to the medium-sized group category.

Evaluation and benchmarking is based on six smart city characteristics signalled by 28 indicators. Almost all indicators are common for both groups of cities. But if in Table 1 there are two indicators in a cell for a particular characteristic, the first one applies to medium-sized cities and the second one to bigger cities. Table 1 lists the six basic smart city characteristics and their indicators that created our data set of 158 European smart or potentially smart cities (77 MSC and 81 LC).

The data set was created manually from the website of European Smart Cities project[2] and we used all available continuous indicators from six key characteristics of smart urban development. All indicators were already in the standardised form (x − mean)/standard deviation. In all, there are 27 indicators measuring the city characteristics for both size groups, and one environmental condition indicator that is only available for MSC. An inspection, or careful control of the data showed that the indicator "Economic image and trademarks" only took a limited range of distinct values for the group of medium-sized cities. For example in 45 out of 77 cases, it took the value −0.497. As this indicator's ability to distinguish between cities` situations appears rather limited we dropped the indicator from our study. As all evaluated cities belong to specific EU member states we can use that fact as a categorical input indicator. In the next parts of the paper, we focus on exploring the specifics of smart cities' development regarding their size, how the level of dominant indicators of smart cities varies in cities of different size.

4. Research results

At first, we present in the Table 2 summary statistical parameters (arithmetic mean, median and standard deviation) of smart cities indicators for both city size groups. In the right column, there are two sided p values of two sample univariate comparisons by Wilcoxon test. Standardisation is useful for some multivariate methods e.g. cluster analysis and factor analysis. It is noteworthy, that for two sample (univariate) comparisons it can hide significant differences.

Location parameters of medium-sized cities in a comparison with larger cities are different in the case of two indicators: ecological awareness (mean, −0.014 vs 0.697, median, −0.144 vs 0.725; $p < 0.001$) and local accessibility (mean, 0.005 vs. 0.187; median, 0.000 vs 0.223, $p = 0.028$). Our research results have shown that both ecological awareness and local accessibility are on average higher in larger cities than in medium-sized cities. Univariate statistical methods showed their limitations in terms of hiding significant difference between two samples, larger and medium sized-cities indicators and in relative importance of predictors for the cities of different size. We can assume that performance of other smart city indicators (except ecological awareness and local accessibility) might differ in the smart cities of different size. This could be an important issue for policy makers and challenge for further research. Efficient and well-oriented focus on enhancement of particular smart cities indicators might have positive impact on the capacity of cities of different size to exploit their growth factors. Our next objective is to find classification of city groups by suitable multivariate statistical model. Standard multivariate classification methods are discriminant analysis and logistic regression. In Table 3 there are the results of a stepwise discriminant analysis.

A stepwise algorithm found six significant indicators - ecological awareness, innovative spirit, touristic attractiveness, ethnic plurality, air quality, and public and social services that are able to distinguish between medium-sized and larger European cities. Table 4 shows that classification was correct more often for larger cities (91.4%) than for medium-sized cities (68.5%). Overall, classification was correct in 80.5% of cases.

Second classification method – logistic regression produced somewhat better results from the viewpoint of correct classification (Table 5). Its forward stepwise algorithm found four significant indicators (ecological awareness, tourist attractiveness, ethnic plurality, and air quality).

Correct classification is, as in the case of discriminant analysis, higher for larger cities (92.6%) than for medium-sized cities (84.2%), as illustrated in the Table 6. Overall, 89.6% of the total sample was correctly classified. This superior classification result could have been anticipated because logistic regression does not require normal distribution of indicators.

We tried to improve correct classification rate between medium-sized and larger cities by modern data mining methodology - decision trees. Due to above mentioned reasons in the section 3, CRT decision tree was the best option for our research investigation. We intended to select the optimal decision tree as simple as possible, with a relatively high overall correct prediction of city size – in at least 90% of cases. The first challenge was to find the decision tree using all the available indicators excluding state (country) - see Fig. 1 below.

It means that all the input indicators were continuous. The CRT decision tree had the default settings: Gini measure, five levels of maximum tree depth, without pruning, surrogate predictor variables for missing values, empirical prior probabilities, and so on.

As seen in Fig. 1, in the first node 0, there are similar numbers of medium-sized and larger cities, 48.7% to 51.3%, where the total number of cities is 158.

If we take all considered indicators one by one (univariate tests) then indicators local accessibility and ecological awareness are better in larger cities than in medium cities, but in decision trees we divide cases (cities) step by step into two disjoint sets by importance of predictors.

The first level and the first division show the influence of the indicator ecological awareness. It is the most significant of all the available indicators. Left node 1, with values of less than or equal to 0.345, contains 77 cities, 79.2% of which are medium-sized. Right node 2, with values higher than 0.345, comprises 81 cities, 80.2% of which are larger cities. This implies that on average larger cities have more pronounced ecological awareness.

We assume that this unexpected feature can be caused by the fact that policy makers, urban planners and finally also citizens and communities in smart cities` pay a lot of attention to the quality of environment. Larger cities usually have to deal with more environmental problems than medium-sized cities caused by higher population density.

At the second level, on the left side of the decision tree, the left node 1 is further divided by the indicator open-mindedness. If its value is less than or equal to - 0.894 then the proportion of larger cities correctly predicted is 100% (terminal node 3). If the value of the indicator is higher, the proportion of medium-sized cities correctly predicted is

[2] http://www.smart-cities.eu/index.php?cid=-1&ver=3

Table 2
Statistic parameters of smart cities available indicators for both size groups.

Indicator	Medium			Larger			
	Mean	Median	Std. dev.	Mean	Median	Std. dev.	p
Innovative spirit	0.040	−0.052	0.7835	0.077	−0.002	0.8704	0.876
Entrepreneurship	0.022	−0.082	0.7467	0.048	−0.039	0.6913	0.714
Productivity	0.015	0.054	0.7128	0.122	−0.005	0.6914	0.299
Flexibility of labour market	−0.081	−0.129	0.8469	−0.242	−0.128	0.9722	0.378
International embeddedness	−0.098	−0.301	0.6768	0.028	−0.287	0.9555	0.726
Level of qualification	0.037	0.066	0.8857	0.163	−0.010	1.0361	0.471
Lifelong learning	−0.056	−0.324	0.8884	0.028	−0.208	0.9121	0.403
Ethnic plurality	0.044	0.032	0.8723	0.059	0.131	0.4642	0.342
Open-mindedness	−0.001	−0.117	0.5299	−0.018	−0.143	0.5800	0.915
Participation public life	0.029	−0.033	0.5962	0.107	0.130	0.7066	0.406
Public and social services	−0.017	−0.007	0.8162	0.012	0.071	0.6160	0.395
Transparent governance	0.000	−0.083	0.7175	−0.009	−0.017	0.6736	0.729
Local accessibility*	0.005	0.000	0.7266	0.187	0.223	0.7805	0.028
(Inter-)national accessibility	0.000	−0.013	1.0000	0.076	−0.073	1.0082	0.793
Availability of IT-Infrastructure	0.005	−0.114	0.7455	0.064	0.127	0.7630	0.414
Sustainability of the transport system	−0.042	0.014	0.5996	0.025	−0.022	0.4147	0.640
Air quality	0.084	0.163	0.6320	0.046	0.185	0.5371	0.411
Ecological awareness**	−0.014	−0.144	0.6663	0.697	0.725	0.4991	0.000
Sustainable resource management	0.030	0.495	0.8484	0.127	−0.082	0.8123	0.880
Cultural facilities	−0.018	−0.138	0.7004	0.023	0.286	0.7539	0.073
Health conditions	0.149	0.176	0.6204	0.187	0.370	0.6954	0.101
Individual security	0.090	0.105	0.7484	0.001	−0.049	0.6913	0.335
Housing quality	0.096	0.076	0.7252	0.091	0.140	0.5413	0.862
Education facilities	−0.033	0.032	0.5856	−0.006	−0.062	0.5740	0.863
Touristic attractiveness	0.000	−0.111	1.0001	0.017	−0.089	0.6077	0.234
Economic welfare	−0.025	0.028	0.7559	−0.045	0.007	0.6952	0.969

Location parameters of medium-sized cities in a comparison with larger cities are different in the case of two indicators: ecological awareness and local accessibility (in bold) with $p < 0.03$ marked by asterisks.

Table 3
Results of stepwise discriminant analysis of classification between MSC and LC.

Entered	Wilks' Lambda							
	Statistic	df1	df2	df3	Exact F			
					Statistic	df1	df2	Sig.
Ecological awareness	0.674	1	1	104	50.365	1	104	0.000
Innovative spirit	0.585	2	1	104	36.577	2	103	0.000
Touristic attractiveness	0.519	3	1	104	31.450	3	102	0.000
Ethnic plurality	0.489	4	1	104	26.387	4	101	0.000
Air quality	0.468	5	1	104	22.701	5	100	0.000
Public and social services	0.448	6	1	104	20.370	6	99	0.000

Table 4
Classification table of stepwise discriminant analysis of classification between MSC and LC.

Observed	Predicted		% correct
	Medium	Larger	
Medium	50	23	68.5
Larger	7	74	91.4
Overall %			80.5

Table 5
Results of stepwise logistic regression of classification between MSC and LC.

Indicators	B	S.E.	Wald	df	Sig.
Ecological awareness	5.496	1.101	24.933	1	0.000
Touristic attractiveness	−2.094	0.627	11.149	1	0.001
Ethnic plurality	−2.080	0.654	10.132	1	0.001
Air quality	−2.457	0.793	9.593	1	0.002
Constant	−0.224	0.390	0.328	1	0.567

Table 6
Classification table of stepwise logistic regression of classification between MSC and LC.

Observed	Predicted		% correct
	Medium	Larger	
Medium	32	6	84.2
Larger	5	63	92.6
Overall %			89.6

84.7% (node 4). Most unexpectedly, medium-sized cities are more open-minded than larger cities. This overturns the conventional view that larger cities are more open-minded. Our results show that larger smart cities predictably exhibit greater ethnic plurality (node 9 and 10), but not higher level of open-mindedness. Two possible reasons spring to mind. First is, that larger cities may be more attractive for different ethnic groups searching for new perspectives, jobs or better enforcement. Integration of new ethnic groups with native citizens may not always go smoothly, esp. in bigger cities with higher density of population. Different problems with the integration of minorities may be the reason of relatively low open-mindedness scores in bigger cities. Secondly, life in larger cities is much more anonymous, with a more fragmented sense of community. The message for policy makers and urban planners is that open-mindedness cannot be perceived as a matter of course. Open-mindedness of urban population should be treated as a fragile plant.

At the second level, on the right side, the right node 2 is further divided by the indicator housing quality. If the value is less than or equal to 0.94, then the proportion of larger cities correctly predicted is 87.5% (terminal node 5). If it is higher than 0.94 the proportion of medium cities correctly predicted is 77.8% (terminal node 6). The interpretation is that larger cities have poorer quality of housing than medium-sized cities. It can be associated with the human density of the larger cities and especially negative aspects of metropolitan life, e.g. traffic jams, higher rate of criminality or lower ability to find the

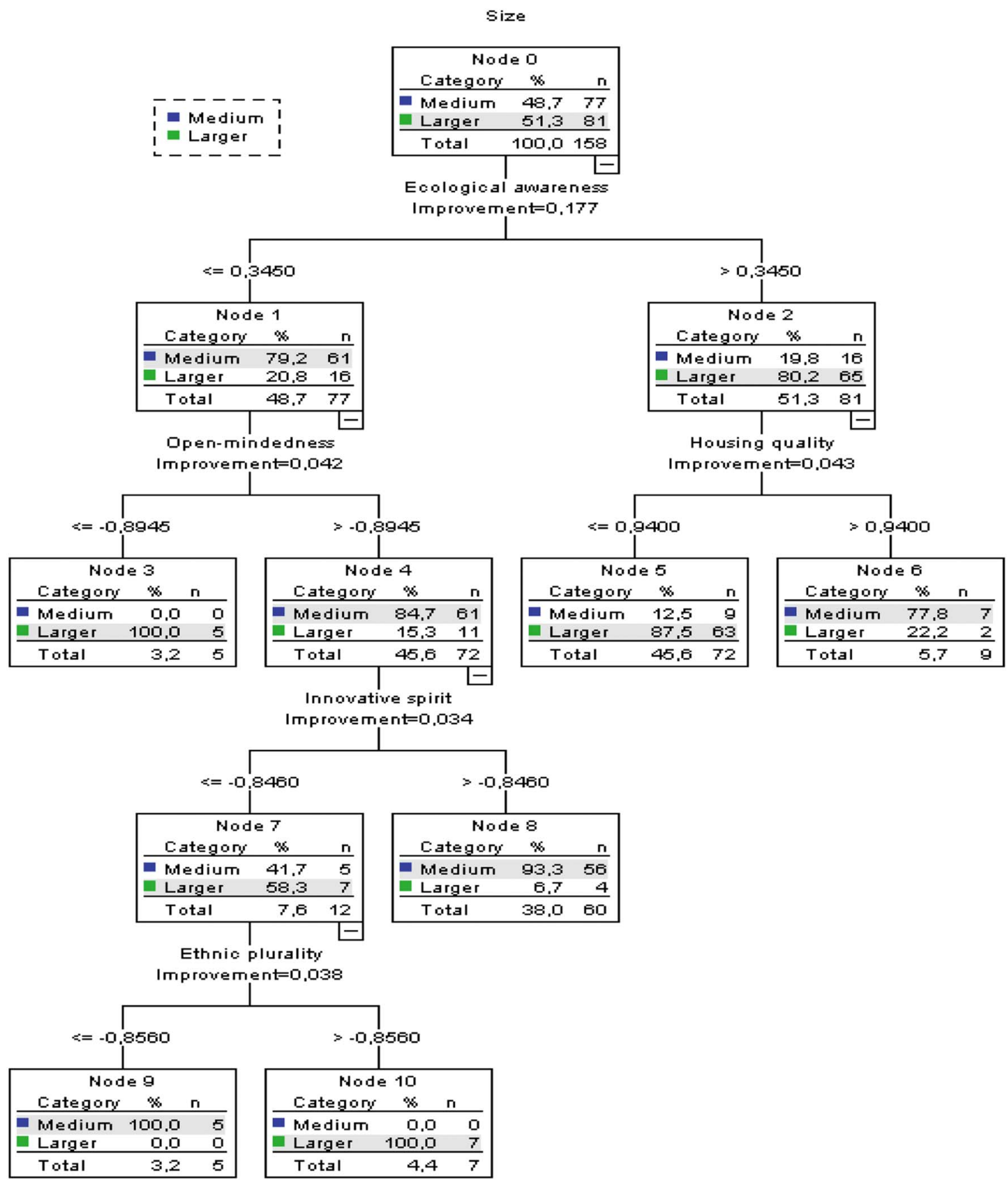

Fig. 1. CRT decision tree of classification between medium-sized cities and larger cities based on continuous indicators.

suitable housing because of the high claims of inhabitants (Vitálišová, Vaňová, Borseková, & Cole, 2016).

At the third level, node 4 is further divided by the indicator innovative spirit into 12 cities with values under −0.846 (node 7) and 60 cities with higher indicator values. The proportion of medium-sized cities correctly predicted is 93.3% (terminal node 8). Medium-sized cities have greater innovative spirit than larger cities – a very important finding. The fact, that medium-sized cities have greater innovative spirit than larger cities, can be caused by the simple preference of innovators and representatives of creative class not to live rush and busy life of a big city. In the 21st century, medium-sized or even small cities can offer comparable living and working conditions to large cities, but at lower cost, and in a more comfortable environment. Many creative workers, freelancers, entrepreneurs and innovators do not need to live in a bustling large city. Their innovative spirit can also flourish in medium-sized cities with an appropriate infrastructure. This is an important message for urban planners and policy makers.

At the fourth level, the final division is made by the indicator ethnic plurality. The left node 9 comprises cities with lower ethnic plurality. The proportion of medium-sized cities is 100% at terminal node 9. The right node 10 comprises cities with higher ethnic plurality. The proportion of larger cities correctly predicted is 100% at terminal node 10. Predictably, larger cities have greater ethnic plurality.

To conclude, left size of decision tree shows us that most of the cities with ecological awareness smaller than 0.345 (number of cities = 77) are medium-sized cities with open-mindedness larger than 0.8945 (node 4). From them there are 60 cities with larger innovative spirit (node 8) and with dominant medium-sized cities (56/60).

The classification Table 7 shows that the CRT model correctly classifies 90.5% of the cities (medium cities 88.3%; larger cities 92.6%)

Table 7
CRT decision tree matrix of smart cities classification.

Observed	Predicted		
	Medium	Larger	Correct %
Medium	68	9	88.3%
Larger	6	75	92.6%
Overall %	46.8%	53.2%	90.5%

according to their size, using the five indicators: ecological awareness, open-mindedness, housing quality, innovative spirit, and ethnic plurality. Correct classification by CRT decision tree model is somewhat better than in the case of logistic regression.

The relative importance of all the predictors involved in the CRT decision tree model is shown in Fig. 2.

The most effective predictor of city size is ecological awareness. The next two predictors, sustainable resource management and tourist attractiveness, are roughly only half as important. In fourth place is open-mindedness with a value of 42%, and this is followed by six other indicators of gradually decreasing importance with values around 30%. As is evident from the figure, several indicators are < 10% of relative importance, including international accessibility, life-long learning, air quality, entrepreneurship, and education facilities.

An important advantage of decision tree modelling is its ability to exploit categorical predictors with many string values, which is usually problematic in classic multivariate methods. In the following CRT decision tree, we used all the available continuous indicators and the categorical predictor, State. The final decision tree is shown in the Fig. 3. At the beginning, in node 0 the proportion of medium to larger cities is 48.7% to 51.3%. The total number of cities involved is 158.

The first level is the same as is it is in the case of the decision tree without state. The first division is made by the ecological awareness variable. It is the most significant predictor. The left node 1, with values less than or equal to 0.345 contains 77 cities with proportion of medium cities at 79.2%. The right node 2, with values larger than 0.345, contains 81 cities with the dominant proportion of larger cities at 80.2%. On average, larger cities exhibit greater ecological awareness.

At the second level, the predictor variable state is on both sides. On the left side of the decision tree node 3 is further divided by the state variable. If cities belong to any of the following states: Bulgaria, Czech Republic, Italy, Poland, Portugal and Slovakia then the proportion of medium cities is 56.8% (37 cities, node 3). But if they belong to Austria, Belgium, Germany, Estonia, Spain, Finland, Hungary, Ireland, Lithuania, Latvia, the Netherlands, Romania or the United Kingdom then the proportion of correctly assigned medium-sized cities is 100% (40 cities, terminal node 4).

On the right side, the right node 2 is further divided by the state variable (Denmark, France, Greece, Luxembourg, Sweden and Slovenia) into fifty-fifty proportions (32 cities, node 5). On the right side there are 49 cities. All are larger cities from the following states: Belgium, Czech Republic, Germany, Estonia, Spain, Finland, Ireland, Italy, Lithuania, Latvia, Netherlands, Poland, Romania and the United Kingdom (proportion 100%, terminal node 6).

At the third level node 3 is divided by ecological awareness into 20 medium-sized cities with values under -0.532 (proportion 100%, terminal node 7), and 17 cities with a correctly assigned proportion of larger cities of 94.1% (terminal node 8). Larger cities on average have higher ecological awareness. Node 5 is divided by sustainable resource management into 17 cities with values under 0.802 (proportion of medium cities 82.4%, terminal node 9) and 15 cities with a correctly assigned proportion of larger cities of 86.7% (terminal node 10). Larger cities benefit from better sustainable resource management.

An interesting statistical result is the existence of a 100% classification at node 4 there are 40 medium-sized cities from 13 countries - Austria, Belgium, Germany, Estonia, Spain, Finland, Hungary, Ireland, Lithuania, Latvia, Netherlands, Romania and United Kingdom. At node 6 there are 49 larger cities from 14 countries - Belgium, Czech Republic, Germany, Estonia, Spain, Finland, Ireland, Italy, Lithuania, Latvia, Netherlands, Poland, Romania and United Kingdom. This result is based on only two prediction variables: ecological awareness, and almost the same group of states, 11 states appear in both groups. Given a group of 89 cities these predictors can identify with 100% success whether a city is medium-sized or larger city.

The classification in Table 8 shows that the CRT model correctly classifies 96.2% of the cities - 96.1% of medium-sized cities, and 96.3% of large cities, using only three indicators: ecological awareness (twice), state, and sustainable resource management. This is excellent classification result from a statistical point of view.

The relative importance of all the predictors involved in the CRT decision tree models is illustrated in the Table 9. The most important predictor of city size is again ecological awareness. The next two most important predictors, sustainable resource management and tourist attractiveness are almost of equal importance, closely followed by the state variable.

For comparison, we also show the original rank of the indicators, with state excluded, and the difference in ranks. Differences larger than five are shown in bold. If the difference is negative then the inclusion of the state variable reduced the indicator variable. If it is positive then the opposite is true. The largest loss in importance is for the public and social services and the participation in public life variables, followed by productivity, local accessibility and innovative spirit. The largest gains in importance are recorded by the air quality, health conditions and sustainability of transport system variables.

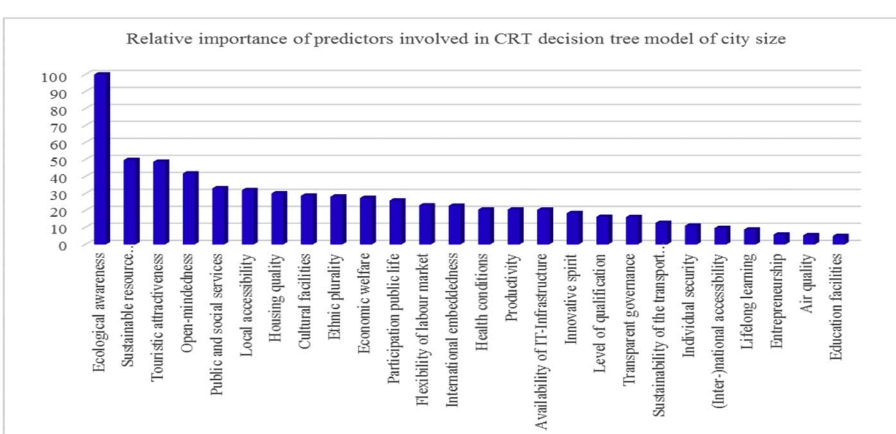

Fig. 2. Relative importance of predictors involved in CRT decision tree model of city size.

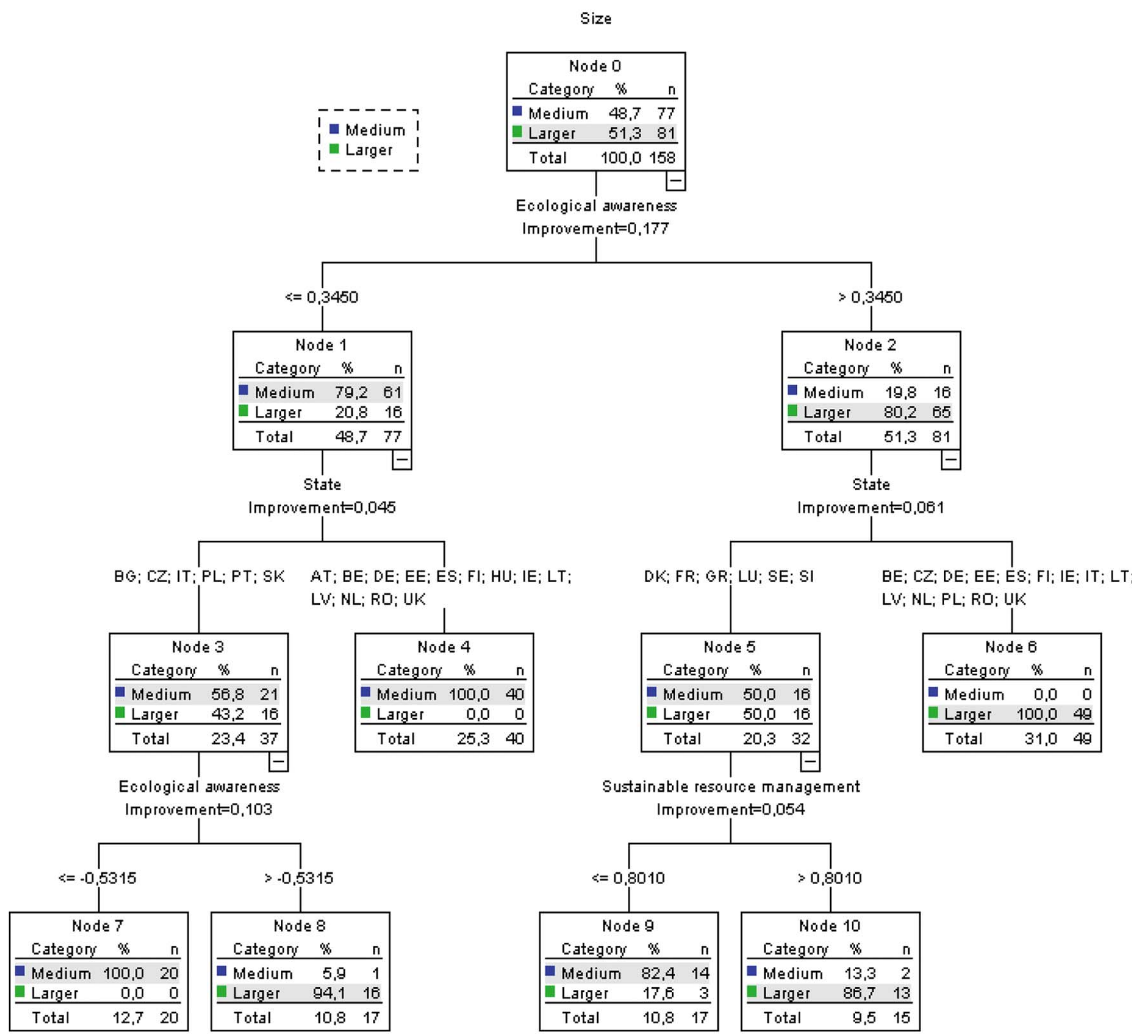

Fig. 3. CRT decision tree of classification between medium-sized and large cities based on continuous indicators and the additional categorical predictor state (country).

Table 8
CRT decision tree classification matrix of smart cities including the factor state.

Observed	Predicted		
	Medium	Large	Correct %
Medium	74	3	96.1%
Large	3	78	96.3%
Overall %.	48.7%	51.3%	96.2%

Based on these results, urban planners, policy makers and representatives responsible for urban development may exploit these results in term of planning their priorities, formulating urban development goals and partial development objectives.

5. Discussion

In the previous section, we set out the most important analytical results. Using CRT decision tree models, we identified the most important predictors of city size among smart city indicators. We showed that the most important predictor was ecological awareness, regardless of whether the state variable was present. It was noteworthy that, on average, ecological awareness is higher in larger cities. However, as we were investigating smart cities we can assume that both groups of medium-sized and large cities have good ecological awareness. Normally, medium-sized cities have better environmental and living conditions than large cities. Therefore, we might expect the former to show greater ecological awareness. Our research shows this is untrue for smart cities. Our favoured explanation is that smart cities` policy makers, urban planners, and their inhabitants pay a lot of attention to the quality of their environments. Larger cities have greater environmental problems than medium-sized cities, partly because of the size of their population and certainly if they have higher population densities. Our results also showed that larger cities benefit from better sustainable resource management, which may explain different ecological awareness in the bigger cities and medium-sized cities. A future research challenge is to explore the relation between ecological awareness and environmental conditions in smart cities and non-smart cities of all sizes.

Very interesting finding in our paper was that medium-sized cities have more innovative spirit than larger cities. This has research and policy implications. Innovators and members of creative classes may prefer not to live in metropolitan areas or larger cities. And in a world where the internet of things is starting to play an important role, living in a big city ceases to be an essential precondition of success. In 21st century, medium-sized with appropriate infrastructure (soft and hard) may be fully competitive to larger cities in terms of attracting creative and innovative workers. This is an important message for urban planners and policy makers. An interesting research challenge is to discover if there is a minimum size for city to exhibit a significant level of innovative spirit.

Our third noteworthy research result is that medium-sized cities are

Table 9
Relative importance of predictors in CRT decision tree models of city size.

Rank	Rank with State	Diff	Independent variable	Importance (%)
1	1	0	Ecological awareness	100.0
2	2	0	Sustainable resource management	47.2
3	3	0	Touristic attractiveness	46.5
–	4	–	State	44.5
4	5	−1	Open-mindedness	34.5
14	6	**8**	Health conditions	29.3
25	7	**18**	Air quality	27.4
10	8	2	Economic welfare	27.0
7	9	−2	Housing quality	24.9
9	10	−1	Ethnic plurality	24.8
8	11	−3	Cultural facilities	23.8
16	12	4	Availability of IT-infrastructure	23.8
6	13	**−7**	Local accessibility	23.0
20	14	**6**	Sustainability of the transport system	22.0
5	15	**−10**	Public and social services	21.1
19	16	3	Transparent governance	21.0
12	17	−5	Flexibility of labour market	20.5
13	18	−5	International embeddedness	20.5
21	19	2	Individual security	19.4
18	20	−2	Level of qualification	18.0
11	21	**−10**	Participation public life	15.7
23	22	1	Lifelong learning	15.3
15	23	**−8**	Productivity	14.0
17	24	**−7**	Innovative spirit	13.2
24	25	−1	Entrepreneurship	13.2
22	26	−4	(Inter-)national accessibility	12.4
26	27	−1	Education facilities	7.7

Differences larger than five are shown in bold.

more open-minded than large cities. This overturns the conventional view that larger cities are more open- minded. Policy makers and urban planners in larger smart cities should not take open-mindedness as a given. In the present unstable world, maintaining open-mindedness in all sizes of smart cities may soon be one of the biggest challenges.

6. Conclusion, research and policy challenges

Besides above mentioned interesting and challenging research results, our paper contains several original ideas, excellent statistical results and contribution to literature and practice in terms of future urban planning and decision making.

Considering existing knowledge and experience from academia and practice, we can identify two approaches in the definition of smart cities. The first approach may be defined as technocratic. Technocratic approach is based on the preference of technical solutions, in particular the use of modern ICTs and their massive exploitation in urban planning. From our point of view, this technocratic approach refers mainly to ‘digital’, ‘cyber’ (for more information see Scott, 2016) or ‘intelligent’ cities (see for example Komninos, 2002, 2013; Paskaleva, 2014). Second approach may be defined as integrated approach. Besides the role of ICT, integrated approach advocate the importance of human aspect (inter alia Caragliu et al., 2011, 2014, Dameri, 2017, Dameri, Sabroux, & Negre, 2016, Giffinger et al., 2007, Hollands, 2008, Nam & Pardo, 2011). In principle, we can talk about smart solutions that concern management, organization and processes. We incline towards integrated approach because of its complexity and orientation on integrity, not only partial technical solutions. In coherence with above mentioned is an approach that adopts European Parliament (2014). The evolution of each particular smart city is shaped by a complex mix of technologies, social and economic factors, governance arrangements, policy and business drivers. The implementation of the Smart City concept, therefore, follows very varied paths depending on each city's specific policies, objectives, but also size, funding and scope. Big investment into ICT, as required in technocratic approach, may not always be the best or the most efficient solution for smaller and medium-sized smart cities. Return of such investments may not always be reliable for smart cities of smaller size. This is the first added value of our paper in terms of enriching current theoretical knowledge on smart cities. Besides, the paper contributes to the literature in following important ways. Although there are several studies that investigate the relationship between urbanization and economic growth, this particular paper analyses the so far understudied relationship between city size and smart cities performance. Another contribution to literature relates to the analysis of significant indicators that allow division of smart cities into size categories. More precisely, the paper explores how the city size shaped individual components (characteristics and indicators) of smart cities.

The scientific originality of our paper may be perceived also from the statistical point of view in excellence of classification results. Correct classification rate on the level of 96.2% by using CRT decision tree based on only three indicators (ecological awareness, state, and sustainable resource management) can divide smart cities into size categories. This is an excellent and unique classification result based on real empirical data.

Our research results lead us to outline interesting future research question*: What is the optimal size of the city for high quality smart city performance?* The implication of Kuznets curve (for more information see inter alia Galbraith, 2007, Kuznets, 1955, Stiglitz, 1996) may be used to test this proposition, as outlined on the picture below (Fig. 4).

To test this proposition is a real research challenge for the future and may lead to interesting research results on smart cities and cities performance in general. These future research results may be also very relevant for policy and decision makers and urban planners.

A great deal of studies and practices address smart city issues at the level of large cities or metropolitan areas. This is a logical reason in terms of fact that larger cities have more money to invest in new technologies. Bigger cities are more interesting from a business perspective in terms of the amount of investment and their returns. Of course, market size is more interesting as well. On the other hand, if we consider the importance of small and medium-sized cities, we may assume that it is crucial to pay more attention to this size category in new and modern concepts or urban development. Small and particularly medium-sized cities are constantly forced to seek for new impulses of development and efficient use of internal resources. Smart city concept might be for them an efficient and suitable approach of urban development. Our research results have shown that there is no disadvantage in building smart cities for medium-sized cities in comparison with bigger cities. This is an important message for policy makers, urban planners and representatives of urban development.

Different European cities following concept of smart city have to face different challenges. For their better understanding, the research in medium-sized cities is crucial. In metropolitan areas and agglomerations, due to synergic and multiply effects, it is not fully possible to identify which indicator has the development impact. Thus, it is sometimes very difficult to identify an originator of desired change correctly. In contrast, in small and medium-sized cites it is possible to identify concrete development impulses better due to their size and

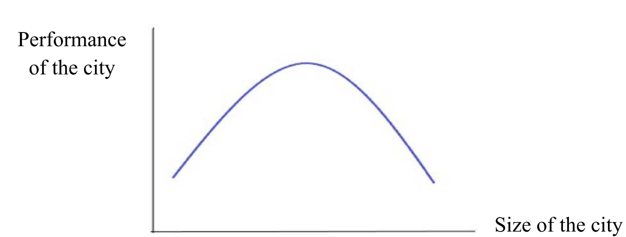

Fig. 4. Performance of smart city in relation to size of the city.

character. The wise combination of technological and non-technological solutions may bring very interesting results in terms of more efficient use of financial resources and in better satisfying needs of urban customers (citizens, tourists, entrepreneurs, etc.).

As mentioned in previous sections, there are almost no studies and relevant literature dedicated to relation between size of the city and smart city indicators. This paper can be considered as one of the first applied modelling studies in this area, which is its added value. Our research results using factorial analysis apply to European countries. Nevertheless, both results and methodology can be an inspiration for the larger future research task, to enhance the theory and practice of smart cities.

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