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BUSINESS AND ARTIFICIAL INTELLIGENCE

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FACULTY OF ORGANIZATIONAL SCIENCES

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Dušan Starčević, Ph.D.
Sanja Marinković, Ph.D.

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FOREWORD

We are very pleased to present the Proceedings of the XVII International Symposium of Organizational Sciences – SymOrg 2020.

Ever since 1989, the Faculty of Organizational Sciences, University of Belgrade, has been the host of SymOrg, an event that promotes scientific disciplines of organizing and managing a business. Traditionally, the Symposium has been an opportunity for its participants to share and exchange both academic and practical knowledge and experience in a pleasant and creative atmosphere. This time, however, due the challenging situation regarding the COVID-19 pandemic, we have decided that all the essential activities planned for the International Symposium SymOrg 2020 should be carried out online between the 7th and the 9th of September 2020.

We are very pleased that the topic of SymOrg 2020, "Business and Artificial Intelligence", attracted researchers from different institutions, both in Serbia and abroad. Why is artificial intelligence a disruptive technology? Simply because "it significantly alters the way consumers, industries, or businesses operate." According to the European Commission document titled Artificial Intelligence for Europe 2018, AI is a key disruptive technology that has just begun to reshape the world. The Government of the Republic of Serbia has also recognized the importance of AI for the further development of its economy and society and has prepared an AI Development Strategy for the period between 2020 and 2025. The first step has already been made: the Science Fund of the Republic of Serbia, after a public call, has selected and financed twelve AI projects.
This year, more than 200 scholars and practitioners authored and co-authored the 94 scientific and research papers that had been accepted for publication in the Proceedings. All the contributions to the Proceedings are classified into the following 11 sections:

Information Systems and Technologies in the Era of Digital Transformation
Smart Business Models and Processes
Entrepreneurship, Innovation and Sustainable Development
Smart Environment for Marketing and Communications
Digital Human Resource Management
Smart E-Business
Quality 4.0 and International Standards
Application of Artificial Intelligence in Project Management
Digital and Lean Operations Management
Transformation of Financial Services
Methods and Applications of Data Science in Business and Society

We are very grateful to our distinguished keynote speakers: Prof. Moshe Vardi, Rice University, USA, Prof. Blaž Zupan, University of Ljubljana, Slovenia, Prof. Vladan Devedžić, University of Belgrade, Serbia, Milica Đurić-Jovičić, PhD, Director, Science Fund of the Republic of Serbia, and Harri Ketamo, PhD, Founder & Chairman of HeadAI ltd., Finland. Also, special thanks to Prof. Dragan Vukmirović, University of Belgrade, Serbia and Prof. Zoran Ševarac, University of Belgrade, Serbia for organizing workshops in fields of Data Science and Machine Learning and to Prof. Rade Matić, Belgrade Business and Arts Academy of Applied Studies and Milan Dobrota, PhD, CEO at Agremo, Serbia, for their valuable contribution in presenting Serbian experiences in the field of AI.

The Faculty of Organizational Sciences would to express its gratitude to the Ministry of Education, Science and Technological Development and all the individuals who have supported and contributed to the organization of the Symposium. We are particularly grateful to the contributors and reviewers who made this issue possible. But above all, we are especially thankful to the authors and presenters for making the SymOrg 2020 a success!

Belgrade, September 9, 2020

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PREDICTING OF CITIZENS' WELL-BEING IN LARGE CITIES

Vladimir Urošević[1], Predrag Jovanović[2], Ivana Ostojić*[2]
[1]Belit Ltd, Belgrade, Serbia
[2]Institute of Social Sciences, Center for Economic Research, Belgrade, Serbia
*Corresponding author, e-mail: ivanaostojic27@yahoo.com

Abstract: *The well-being of citizens in large cities is an important issue due to potential gaps between needs and capacities for providing health care. That became particularly visible during the Covid pandemic. Thus identifying factors of citizens' well-being in large cities and based on that developing a model of its improvement is of high significance. In the paper six relevant sub-domains of well-being were identified: Evaluative, Emotional, Functional, Vitality, Community, and Supportive. Three of them: Emotional well-being, Evaluative well-being, and Functioning appeared to be highly correlated with each other. The three of the most predictive features of well-being proved to be the presence of anxiety or depression feelings (Anxiety/depression), the presence of pain or discomfort (Pain/discomfort), and the general self-evaluation of health status in the day the participants respond (Health scale). The results of this research may serve local self-governments to get insights into citizens' well-being and to predict changes in the future.*

Keywords: *well-being, wearable trackers data, prediction, physical activity, health*

1. INTRODUCTION

The world is faced with a very intense process of urbanization. It is foreseen that in 2050, 68% of the population will live in the cities. Nowadays, cities generate 75% of the carbon emission, which means the urban population is highly exposed to pollutants (United Nations Development Programme, 2020). The World Health Organization (WHO) estimates that 63% of global mortality (about 36 million deaths per year) is the result of non-communicable diseases (e.g., cardiovascular disease, cancer, diabetes, and lung disease) that are attributable to the increased exposure to air pollution concentration and an inactive lifestyle (World Health Organization, 2016). Elder citizens are particularly vulnerable to those negative factors.

Demographic trends in EU countries are characterized by a growing share of older adults. Increasing needs of elder citizens' care created pressure on local governments' resources. The stress was even more visible in emergency situations such as the COVID pandemic. For that reason, it is necessary to improve the management of healthcare system resources in order to meet increasing demand in particular in highly populated large cities. In this sense, smart cities may be the new concept that would help EU countries to respond to the needs of their changing population, increasing the efficiency of the resources, while improves the quality of life of citizens (Pierce, 2017). This is especially important for aging syndromes, such as frailty, in which prompt detection can prevent, even reverse, this condition, improving life expectancies of the affected individuals (Abril-Jiménez, 2019).

Frailty may be considered as a vulnerable status, which can precede the onset of overt disability. Structured exercise programs are effective in contrasting the progression of frailty, but a healthy and active lifestyle may be sufficient for delaying the onset of disability (Abate, 2007). Recent researches confirmed that active individuals have been related to lower rates of developing frailty (McPhee, 2016).The situation has driven to consider as a priority the need to create tools, guidelines, and recommendations to enable healthier, climate-friendly, and resilient lifestyles within urban environments (World Health Organization, 2019).

The European funded project PULSE (Participatory Urban Living for Sustainable Environments) aims to study the relationship between well-being and its predictors under a quantitative point of view, so a feature assumed as a possible predictor must be transformed into a well-identified and measurable concept. Under this quantitative approach, the main interest of the study is intended to be the detection of features that significantly affect well-being (PULSE, 2020).

Most of the identified predictors are related to the habits of participants about food, self-care, relationships with other people, physical activity, and their health status both at a physical and psychological level. The tools used to collect data were:

- Self-compiled questionnaires: Profile, Basic socio-demographics, Neighborhood environment, Health behaviors and habits, Physical activity IPAQ-Short, EuroQol-5d, Generalized anxiety disorder, Patient health questionnaire-9.
- Wearable trackers (Fitbit, ASUS, and Garmin) that allowed the recording of some biometric variables mainly regarding sleep quality and physical activity.

In this paper, the data collected by the above-mentioned sources will be explained from the raw information they provide, up to the way in which this information has been transformed and used in the fitting of machine learning models. The machine learning models that have been used in the paper are introduced and subsequently, the results of the analysis are presented.

2. QUESTIONNARIES DATA

In this research, the Well-being and the European Social Survey (WES) questionnaire has been used in an adjusted version to obtain an assessment of well-being status of participants. This questionnaire provides a direct measure of the general well-being status of participants, based on their feelings and perceptions, and it is reasonable to think that it is one of the most effective methods for measuring of the actual state of well-being (European Social Survey, 2020). However, it is worth considering that it does not represent an absolute and objective measure, since the individual responses to the questionnaire are, by rule, characterized by a subjective bias.

WES questionnaire is made up of 15 items monitoring 6 different dimensions of well-being (European Social Survey, 2020):

- **Evaluative well-being :**
  I'm satisfied with life as a whole
  I'm happy with my life
- **Emotional well-being:**
  I enjoy my life
  I feel calm and peaceful
- **Functioning:**
  I can decide how to live my life
  I have a sense of accomplishment in my life
  I'm optimistic about my future
  I have idea of how my life would be in the future
- **Vitality:**
  I sleep well
  In general, I have lots of energy
- **Community well-being:**
  People in my neighborhood are kind and helpful
  I have friends in my local area
- **Supportive relationships:**
  I feel appreciated by my friends and family
  I receive help and support when I need it
  I trust people in my neighborhood

The possible responses to each item of the WES questionnaire are in a 5 levels scale expressing how much the individual agrees with a statement (in particular, categories are: "Agree strongly", "Agree", "Neither agree nor disagree", "Disagree", "Disagree strongly").

The computation of the 6 dimensions of well-being (and the one referred to overall well-being) is the result of the following steps:

- Conversion to numerical scores as Agree strongly - 4, Agree - 3, Neither agree nor disagree - 2, Disagree - 1 and Disagree strongly - 0.
- Standardization of individual scores (s_{ij}):

$$\overline{s_{ij}} = \frac{s_{ij} - \overline{s_j}}{\sigma_{s_j}} \tag{2}$$

where:

s_{ij} is a subject-specific measure, that is the score obtained for the i-th individual in the j-th item, $\bar{s}_j$ is the mean score for the j-th item of WES questionnaire. It has the same value for each subject that responded to the j-th item. $\bar{s}_j$ is obtained as follows, where n_j is the number of subjects that responded to the j-th item.

$$\bar{s_j} = \frac{\sum_{i=1}^{n_j} s_{ij}}{n_j} \tag{3}$$

where:

σ_{s_j} is the standard deviation of all scores obtained for the j-th item. It has the same value for each subject that responded to the j-th item and it is obtained as follows:

$$\sigma_{s_j} = \sqrt{\frac{\sum_{i=1}^{n_j}(s_{ij} - \bar{s}_j)^2}{n_j}} \tag{4}$$

Assessment of the individual scores for each dimension of interest, using a mean of standardized scores of each item that is included in that dimension.

The concept of well-being that is developed in this research includes above mentioned 6 dimensions and the overall well-being measure. Therefore, the models will be evaluated both for each of the six dimensions and for a more general measure of well-being, given by the mean of the scores obtained on the six dimensions. Table 1 shows summary statistics of the scores obtained for each dimension and their mean in the whole set of collected data.

Table1: Summary of observed scores for well-being dimensions

	Min.	**1st Qu**	**Median**	**Mean**	**3rd Qu**	**Max**	**Std. Dev.**
Evaluative	-3.57	-0.04	-0.03	0	1.13	1.14	0.97
Emotional	-3.07	-0.83	0.23	0	0.80	1.33	0.86
Functioning	-2.99	-0.55	0.01	0	0.54	1.36	0.81
Vitality	-2.44	-0.48	0.04	0	0.50	1.49	0.84
Community	-2.72	-0.57	-0.02	0	0.50	1.58	0.90
Supportive	-3.81	-0.31	0.06	0	0.52	1.34	0.79
Overall	-3.10	-0.37	0.04	0	0.36	1.37	0.66

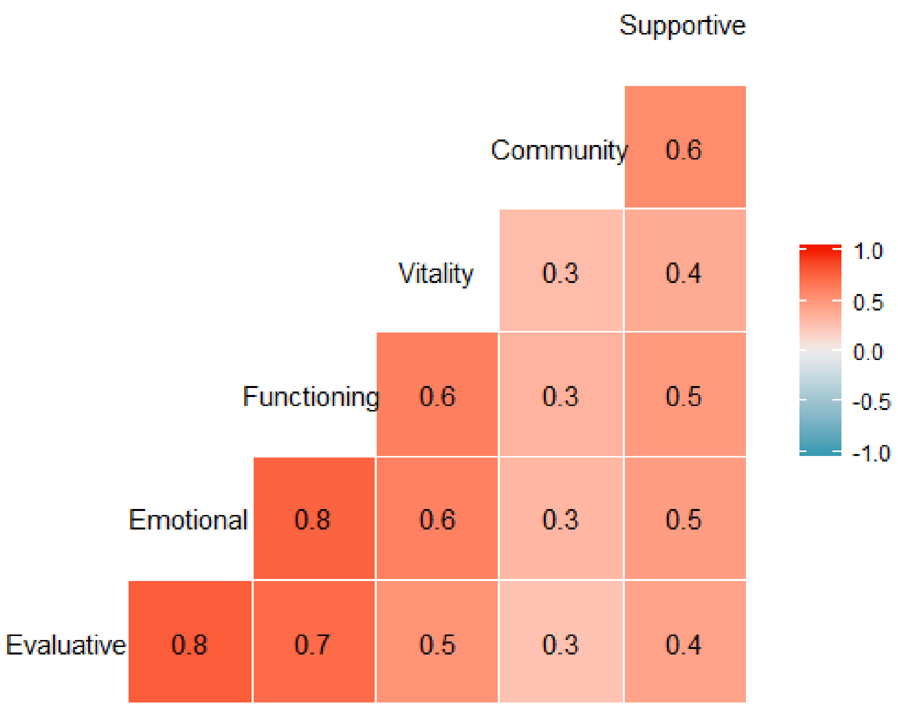

Figure 1: Correlations between well-being dimensions

Figure 1 shows how much the dimensions obtained are correlated to each other, with a darker cell color indicating stronger correlation between the two dimensions. In particular, the dimensions “Emotional well-being”, “Evaluative well-being” and “Functioning” are highly mutually correlated. Although it is difficult to clearly identify why this happens, it could be due to the nature of items that take part to their construction. That is, while other dimensions mostly regard “concrete” aspects of individual life (sleep, friends, trust and support from other people), functioning, emotional and evaluative well-being regard individual feelings about his/her overall life (satisfaction, joy, optimism and accomplishment). In the next section, the statistical tools used to identify the best predictors for each well-being dimension will be presented. Based on them, prediction of the well-being would be possible to be done.

3. PREDICTORS OF WELL-BEING

The second set of variables included in machine learning models were data related to health that were recorded by wearable trackers. The variables covered subjects’ level of physical activity and the quality of their sleep. According to the study of the World Health Organization (WHO), physical inactivity is a leading risk factor for premature death from non-communicable diseases. Conversely, regular physical activity is associated with reduced risks of heart disease, stroke, diabetes, breast and colon cancer, and improved mental health and quality of life (World Health Organization, 2019).

Walking and cycling are key means of transportation enabling people to engage in regular daily physical activity. Sport is an underutilized yet important contributor to physical activity. Physical and health literacy are preconditions for a lifelong healthy, active lifestyle and prevention of non-communicable diseases. World Health Organization considers that policy action on walking, cycling, active recreation, sport and play contribute directly to achieving many of the Sustainable Development Goals.

Unlike physical predictors, quality of sleep is a psychical one. Due to several reasons like frailty, illness, and simply due to their age, among other reasons, older people are at disproportionately higher risk of suffering from mental health problems. What is further noteworthy for all age groups, but especially so for the older adults, is that physical health has an impact on mental health just like mental health has an impact on physical health. Therefore, along with a continued focus on extending their life expectancy, it is also necessary to understand the strategies to maintain the sound mental health of older adults (Kadariya, 2019). Researches confirm that overall better health condition results in a better quality of sleep among other indicators of mental health (Garatachea et al., 2009). And vice versa, inadequate sleep duration may cause severe health problems such as diabetes type 2 for example (Shan et al., 2015).

The data for this research were collected by several types of health and fitness wearable tracker devices manufactured by Fitbit, Garmin and ASUS, monitoring physical and walking activity, sleep and heart/cardio parameters, for over 300 recruited citizens participating in the study in 7 global tested cities (Barcelona, Birmingham, New York, Paris, Pavia (Italy), Singapore, and Keelung/Taipei), selected by the Project PULSE (Urošević et al., 2020).

In recording physical activity, each subject used a wearable tracker. The variables of interest have been recorded daily, for a period of different length for each individual. However, only the recordings temporally close to the data of the first compilation of WES questionnaires have been kept, thus also making the number of observations as homogeneous as possible among subjects. Variables recorded through the wearable tracker devices are all numeric and regarding the health status of participants.

Table 2: Summary of principal component analysis from wearable trackers data

Variable name	Min	Median	Mean	Max	Std. Dev.
Sleep 1	-2.37	1.01	0	3.01	3.27
Sleep 2	-0.74	-0.74	0	3.21	1.21
Sleep 3	-0.10	-0.08	0	2.97	1.10
Sleep 4	-0.25	0.04	0	2.62	0.95
Sleep 5	-0.07	-0.07	0	2.87	0.89
Sleep 6	-0.31	-0.01	0	2.57	0.83
Sleep 7	-0.13	0.03	0	2.08	0.76
Physical activity 1	-3.07	-1.16	0	5.20	3.26
Physical activity 2	-0.93	0.47	0	2.16	1.35
Physical activity 3	-0.49	-0.02	0	2.12	1.16
Physical activity 4	-0.70	0.06	0	2.46	1.00
Physical activity 5	-0.73	0.23	0	2.35	0.96
Physical activity 6	-0.93	0.33	0	2.16	0.91

With the data recorded, 7 principal components have been individuated for the first group (sleep quality) and 6 principal components have been used to summarize information about physical activity, with 75% of variance explained by the principal components in both cases. Some summary measures for the individual components are reported in Table 2.

4. LINEAR REGRESSION MODELS

Linear regression model is a useful tool for prediction of well-being status providing an estimated coefficient for every predictor included in the model. A typical linear model is shown below.

$$\mathrm{Y} = \alpha + \beta_1 \mathrm{Predictor1} + \beta_2 Predictor2 + \cdots \tag{5}$$

Where Y is any of the 7 dimensions of well-being to be predicted, predictor 1 and predictor 2 are some of the input variables deriving from questionnaires, wearable trackers recordings, and β_1, β_2 are the respective coefficients expressing how much the input variable and the output Y are related and in which direction. However, the large number of variables required the use of some shrinkage tool in order to reduce the variance of the estimated coefficients, in the face of a slight increase in their bias. In this context, Lasso tool has been used.

According to lasso shrinkage, the p coefficients, β_j are estimated like in a generic linear model, with the addition of the following constraint:

$$\sum_{j=1}^{p-1} |\beta_j| \leq \lambda \tag{6}$$

Here, *p* is the number of variables included in the model and λ is the element that determines how strong is the constraint, being stronger with a lower λ value. For this reason, it is considered the regularization parameters of lasso penalization. The choice of the best value of λ, for each model referred to a certain dimension of well-being, starts with the detection of a set of possible values for λ.

The transformation performed by lasso is the same for every coefficient, in fact, it could be intended as a translation of coefficients of a certain constant. In addition, lower coefficients are truncated to 0, thus obtaining an effective selection of variables, since in a linear model setting, when the coefficient of a certain variable is close to 0, it means that it does not give any contribution to the model (James et al., 2013).

5. BEST PREDICTORS

One of the significant outputs of the linear regression model with lasso shrinkage was estimated value of its coefficients β that expressed both the strength of the correlation between the input variable to which it was referred and the output Y as well as the direction of this correlation. In particular, the higher is the absolute value of β, the stronger is the linear correlation between the output (the dimension of well-being to which the model is referred) and the input feature to which β is referred.

The three most predictive features among considered dimensions are: 1) the presence of some anxiety or depression feelings (Anxiety/depression), 2) the presence of some pain or discomfort (Pain/discomfort) and 3) the general self-evaluation of health status in the day the participants respond (Health scale). In particular, Anxiety/depression and Pain/discomfort are negatively correlated with all dimensions, which means that high status of Anxiety/depression or Pain/discomfort usually occurs together with low levels of well-being. At the same time, Health scale coefficient is positive which means that high values of Health scale indicates high levels of well-being.

The aim of this paper is to detect the features that are the best predictors of the well-being in a general sense. For that reason we will focus on the relationships between particular predictors on one side and the overall well-being on the other. As we pointed out, Anxiety/depression, Pain/Discomfort and Health scale were identified as the best predictors with average coefficients β respectively equal to -0.30, -0.13, and 0.22.

The results expressed above are summarized in the following formula, including the average estimates of the 10 best predictors for overall well-being:

$$\hat{\mathrm{Y}} = -0.30\mathrm{AD} + 0.22\mathrm{HS} - 0.13\mathrm{Pdis} + 0.08\mathrm{Mar} - 0.07\mathrm{GrGroc} + 0.06\mathrm{UsAct} + 0.05\mathrm{More6} + +0.05\mathrm{Sleep} + 0.05\mathrm{PASMod} + 0.04\mathrm{FreeTP} + \cdots \tag{7}$$

where:

$\hat{Y}$= Predicted value for Overall well-being

AD= Anxiety/Depression

HS= Health scale

Pdis= Pain/Discomfort

Mar= Marital Status Married

GrGroc= Green Groceries Availability

UsAct= Usual Activities

Mora 6= More than 6 drinks per night

Sleep= Sleep hours per night

PAS Mod= Class PAS Moderate

FreeTP= Free time parks

The figures below show the relations between the overall well-being and the values of all ten predictors considered.

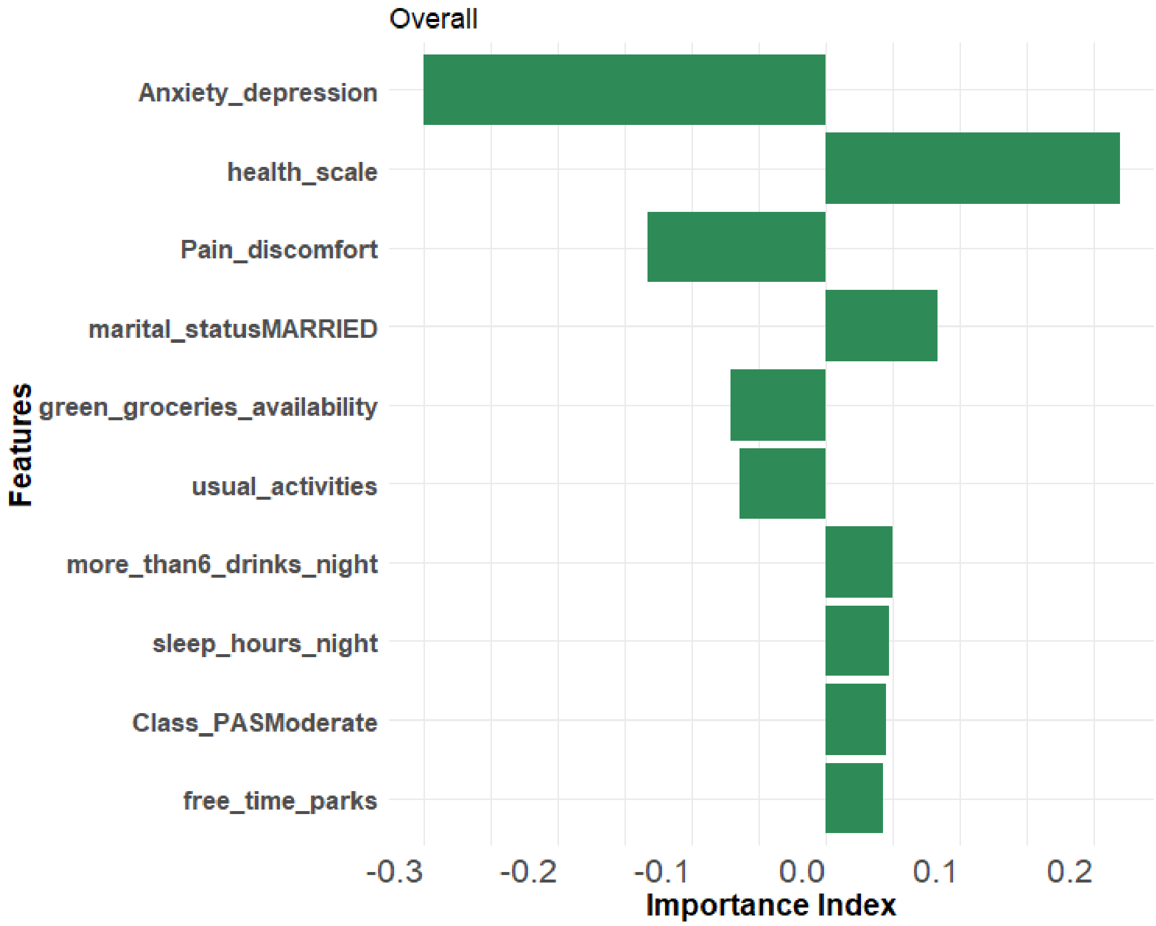

Figure 2: 10 best predictors for overall well-being

The figures below show the relations between the observed overall well-being and the observed values of, respectively, Anxiety/Depression Pain/Discomfort and Health scale. It can be observed that these features appear correlated with overall well-being in the same direction of their respective estimated coefficients. However, it is worth considering that the following figures show the marginal relation with the overall well-being, while the estimated coefficients express the same relationship net of all other variables included in the model.

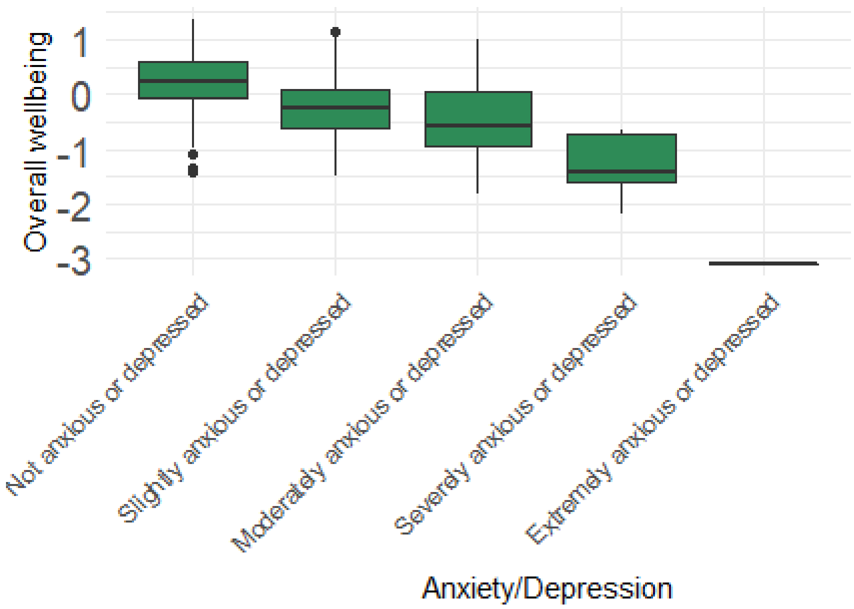

Figure 3: Anxiety/Depression vs Overall well-being on observed data

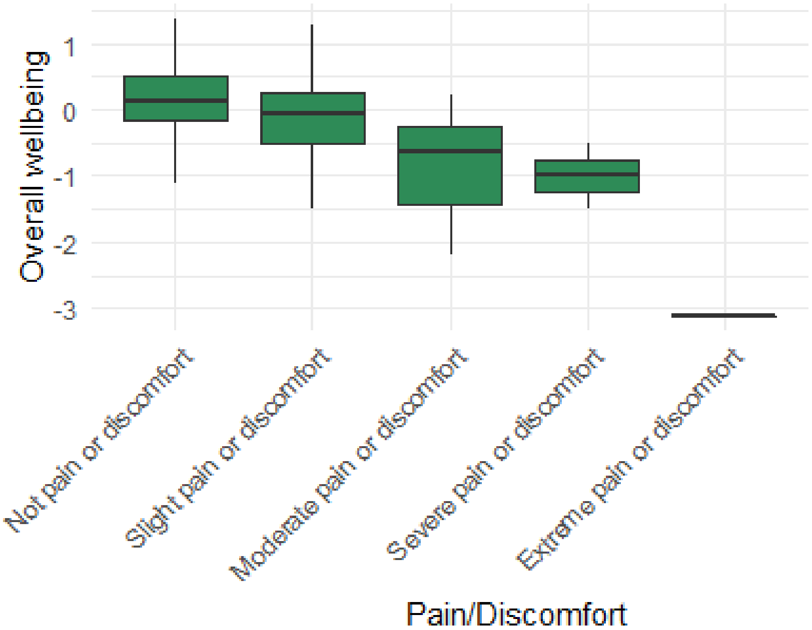

Figure 4: Pain/Discomfort vs Overall well-being on observed data

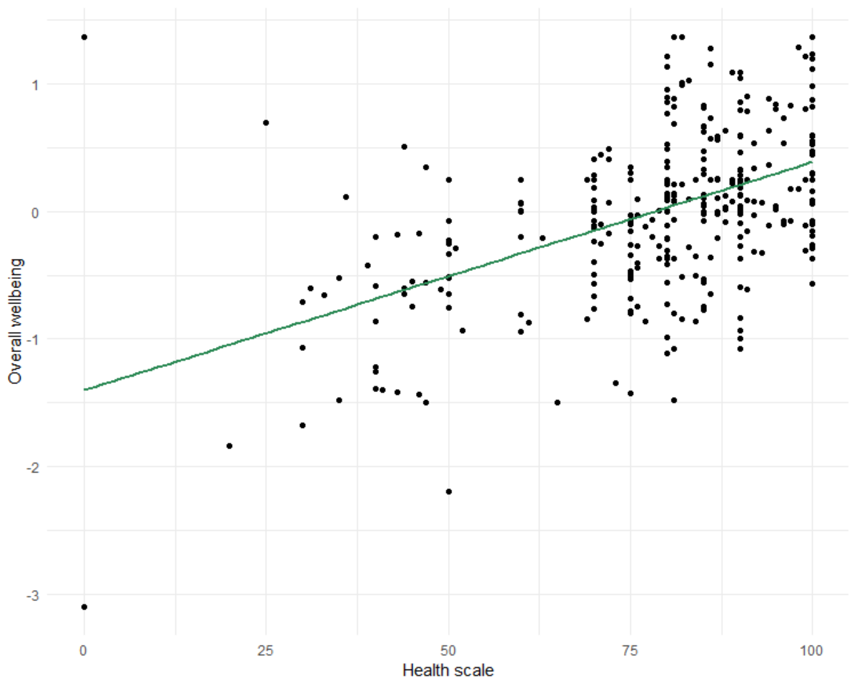

Figure 5: Health scale vs Overall well-being on observed data

6. CONCLUSION

In this paper, the authors tried to detect significant factors of well-being and based on them to develop a prediction model of well-being improvement. This has been done by recording and analyzing of key features of the individual daily life habits of citizens in large cities.

Since well-being is a broad and complex issue, the authors selected six sub-domains: Evaluative, Emotional, Functional, Vitality, Community, and Supportive well-being for the purpose of this research. The prediction model of the six sub-domains confirmed their overall relevance. Moreover, the dimensions Emotional well-being, Evaluative well-being and Functioning were highly correlated with each other.

The three of the most predictive features of well-being proved to be the presence of anxiety or depression feelings (Anxiety/depression), the presence of pain or discomfort (Pain/discomfort), and the general self-evaluation of health status in the day the participants respond (Health scale). In particular, Anxiety/depression and Pain/discomfort are negatively correlated with all dimensions, which means that high status of Anxiety/depression or Pain/discomfort usually occurs together with low levels of well-being. On the contrary, high value of Health scale go hand in hand with a high level of well-being.

The results of this research may serve to local governments to provide composite pictures (i.e. the six scales) of the well-being of the population of the cities. However, it is important to be aware that the relationships detected between well-being on one side and the predicting features on the other have no direct, causal character. In spite of that, the presented model may well serve as monitoring and predictive tools of the well-being, both at a community and at the individual level.

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REFERENCES

[1] Abate, M., Di Iorio, A., Di Renzo, D., Paganelli, R., Saggini, R., & Abate, G. (2007). Frailty in the elderly: the physical dimension. *Europa medicophysica*, *43*(3), 407–415. https://pubmed.ncbi.nlm.nih.gov/17117147/

[2] Abril-Jiménez, P., Lacal, J.R., Pérez, S.D., Páramo, M., Colomer, J.B., & Waldmeyer, M.T. (2019). Ageing-friendly cities for assessing older adults' decline: IoT-based system for continuous monitoring of frailty risks using smart city infrastructure. *Aging Clinical and Experimental Research*, 32, 663 - 671. https://doi.org/10.1007/s40520-019-01238-y

[3] European Social Survey. (2020). Europeans' Wellbeing: Dimensions of Wellbeing. Retrieved from http://www.esswellbeingmatters.org/data/index.html#wellbeing-a-multidimensional-concept-1
[4] Garatachea, N., Molinero, O., Martínez-García, R., Jiménez-Jiménez, R., González-Gallego, J., & Márquez, S. (2009). Feelings of well being in elderly people: relationship to physical activity and physical function. *Archives of gerontology and geriatrics*, *48*(3), 306–312. https://doi.org/10.1016
[5] James, G., Witten, D., Hastie, T., & Tibshirani R. (2013). *An Introduction to Statistical Learning: with Applications in R.* New York :Springer
[6] Kadariya, S., Gautam, R., & Aro, A. R. (2019). Physical activity, mental health and wellbeing among older adults in South and Southeast Asia: A scoping review. *BioMed Research International*, *2019*, [6752182]. https://doi.org/10.1155/2019/6752182
[7] McPhee, J. S., French, D. P., Jackson, D., Nazroo, J., Pendleton, N., & Degens, H. (2016). Physical activity in older age: perspectives for healthy ageing and frailty. *Biogerontology*, *17*(3), 567–580. https://doi.org/10.1007/s10522-016-9641-0
[8] Pierce, P., Ricciardi, F., & Zardini, A. (2017). Smart Cities as Organizational Fields: A Frameworkfor Mapping Sustainability-Enabling Configurations. *Sustainability*, 9(9), 1-21. doi:10.3390/su9091506
[9] PULSE Project. (2020). Participatory Urban Living for Sustainable Environments. H2020-727816, UNIPD
[10] Shan, Z., Ma, H., Xie, M., Yan, P., Guo, Y., Bao, W., Rong, Y., Jackson, C. L., Hu, F. B., & Liu, L. (2015). Sleep duration and risk of type 2 diabetes: a meta-analysis of prospective studies. *Diabetes care*, *38*(3), 529–537. https://doi.org/10.2337/dc14-2073
[11] United Nations Development Programme. (2020). Goal 11: Sustainable cities and communities. Retrieved from https://www.undp.org/content/undp/en/home/sustainable-development-goals/goal-11-sustainable-cities-and-communities.html
[12] United Nations Development Programme. (2020). Department of Economic and Social Affairs. Retrieved from https://www.un.org/development/desa/en/news/population/2018-revision-of-world-urbanization-prospects.html
[13] Urošević, V., Andrić, M., & Pagán, J. (2020). Baseline Modelling and Composite Representation of Unobtrusively (IoT) Sensed Behaviour Changes Related to Urban Physical Well-being, in the process of publishing
[14] World Health Organization. (2016). Ambient Air Pollution: A Global Assessment of Exposure and Burden of Disease. Retrieved from http://www.who.int/iris/handle/10665/250141
[15] World Health Organization. (2019). Sustainable Cities: Health at the Heart of Urban Development. Retrieved from https://www.who.int/sustainable-development/cities/Factsheet-Cities-sustainable-health.pdf?ua=1