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The Impact of the Covid-19 Pandemic on Key Indicators of Personnel Security: A Study with Neural Network Technologies

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Abstarct:

Purpose: *The aim of this paper is to analyze the conceptual foundations of the use of artificial neural networks for highly accurate prediction of personnel security, construction of a mathematical model and building network architecture to solve the problem, as well as providing an example of forecasting and interpretation of results.*
Design/Methodology/Approach: *Assessing the impact of the coronavirus disease (COVID-19) pandemic caused by SARS-CoV-2 on all aspects of human civilization is an urgent scientific challenge today. However, it is already clear that it is human potential that will be impacted most by the pandemic. Using artificial neural networks with radial basis functions, the article predicts the influence of the COVID-19 pandemic on staff turnover, which is one of the most important indicators of personnel security.*
Findings: *The network architecture is built and its mathematical description is made. The main factors influencing staff turnover as one of the main components of personnel security have been defined. Staff turnover in the EU in 2020 and its dependence on the GDP change value has been analyzed.*
Practical Implications: *Personnel security of enterprises and organizations is the basis of economic security nationwide. Nowadays, the Covid-19 pandemic first and foremost hits staff, especially their mental and physical health, thus having a direct impact on the level of personnel security. That is why, in order to effectively prevent a decline in the level of economic security, the impact of the pandemic on key personnel security indicators should be monitored in a timely manner. This is possible then using our metod.*
Originality/Value: *The value of the research is to test the adequacy of the artificial neural network with RBF in predicting the impact of the COVID-19 pandemic on personnel security. It also offers testing the prognostic properties of this type of ANN and considers the possibility of their use for analysis, evaluation and forecasting of socio-economic phenomena and processes.*

Keywords: *Bankruptcy, economic security, external threats, internal threats, staff turnover, neural networks, pandemic, personnel economics, personnel security, safety, technology.*
JEL codes: *C6, I15, M5.*
Paper type: *Research article.*

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1. Introduction

Covid-19 has changed the world forever. People have learned to live alongside the pandemic, developed a vaccine, but have not yet fully understood the depth of irreversible change, such as the transition to a radically different model of economic development. The neoliberal model of economic development, which worked effectively before the pandemic for more than 30 years, proved to be not only ineffective but even utopian in crisis conditions (Kovel, 2007; Krausmann *et al.*, 2013; Brown, 2019). In the conditions of sustainable development, it completely satisfied the post-industrial society with its relative simplicity, because the principles underlying it were reliable and irrefrangible.

Self-regulation of the economy, free competition and unlimited economic freedom provided the planet with material goods, although they had a detrimental effect on the environment. At the same time, the market was considered only as an effective system that promotes economic growth and ensures the priority position of economic entities. The state created conditions for free competition and exercised control only where this competition was lacking (Harel and Gomes-Mera, 2005). With such an approach, Covid-19 immediately began to destroy the world economy. Already at the beginning of 2020, the British FTSE, the American Dow Jones Industrial Average and the Japanese Nikkei 225 dropped by 34.1%, 31.1%, and 28.7% respectively. More than 80 developing countries have applied to the International Monetary Fund for assistance of 2.5 trillion USD (Remarks by IMF Managing Director Kristalina Georgieva at the Meeting of the Ministers of Finance and Central Bank Governors of the Gulf Cooperation Council, 2020).

A new model of the economy, which clearly proves its effectiveness is the one with maximum proximity of business to the state. Its introduction together with vaccination, according to the World Economic Outlook Update in 2021, is expected to result in 5.5% growth of the world economy (World Economic Outlook Update, 2021). However, the threat still remains, as new forms of the virus emerge exponentially. According to the new model of economic development, as noted by the investigators of the subject, over time the percentage of the state economy will increase significantly. Key issues that need to be addressed will include: employment, social security, the creation of a single IT structure, a high level of personnel security and the availability of highly qualified staff who will be able to successfully overcome the new challenges of the time. The latter is impossible without timely forecasting the impact of the pandemic on personnel security indicators, and staff turnover, as its key indicator in particular (Rajasekar and Venkateswara Prasad, 2017; De Winne *et al.,* 2018).

According to recent studies (Liu and Peng, 2010), staff turnover is one of the main indicators of personnel security at both the macro level and that of an individual enterprise. This indicator consists of two components: the actual (real) staff turnover and mental turnover, which in turn depends on a number of external and internal factors, which have been described below and taken into account in the modeling.

It is not possible to make predictions by simple statistical analysis, because the resulting values are influenced by many factors that significantly reduce the accuracy. With this in mind, we used the tools of neural network technologies, as artificial neural networks have proven to be an effective tool for solving complex problems with a high degree of nonlinearity (Shahin and Jaksa, 2006; Isik and Ozden, 2012). The use of artificial neural networks (ANN) with radial-basis transmission functions (RBF) allows highly accurate and fast assessment and prediction of non-stationary processes and socio-economic phenomena, between which there are nonlinear relationships.

2. Research Methodology

The methodology for predicting the impact of the Covid-19 pandemic on key personnel safety indicators is based on ANN with RBF, as they provide high learning speeds. In addition, the radial-basis network is characterized by three features, namely:

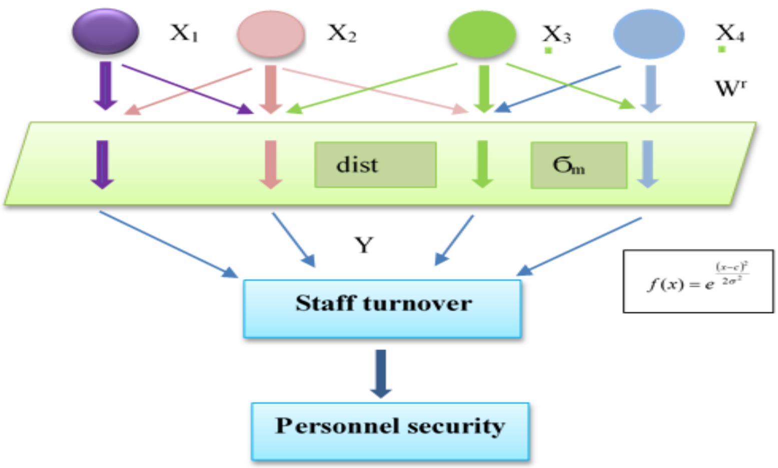
- a single hidden layer;
- nonlinear activation function of the hidden layer neurons only;
- synaptic weights of the connections of the input and hidden layers are equal to one.

It should be noted that the radial-basis transmission function is a function of a set of similar radial functions, which takes as an argument the distance between the input vector and some predetermined center of the activation function, in other words performs the activation function in one layer of the neural network. The closer to the center the input vector is, the higher is the value of this function. To predict the impact of the Covid-19 pandemic on key indicators of personnel security, the appropriate network architecture was built, which consists of input, single hidden (radial-basis) and linear (output) layers (Figure 1).

The input layer consists of sensors, so-called synaptic contacts that connect the network to the external environment and, accordingly, respond to changes in this external environment. The type of response was set when teaching the network using existing data, and the chosen type of learning, "by the teacher's method" in MATLAB environment with a multi-step algorithm to improve prediction accuracy, as it forms a model with the optimal number of hidden layer neurons.

Thus, a two-level network was created with the first level of radial-base neurons, which calculated its weighted inputs using the Euclidean distance function dist, as well as its specific inputs. The second level consisted of simple linear neurons ($y = f(x) = x$) and calculated its weighted input and its specific inputs using the appropriate functions.

Figure 1. *Artificial neural network architecture for predicting the impact of the Covid-19 pandemic on key personnel security indicators*



Source: *Own elaboration.*

where:

$X = (x_1, x_2, \dots, x_n)$ – vector of network inputs;

(W^r) – weight matrix, which acts as centers;

(dist) – the block in which the Euclidean distance between the input vector (X) and the corresponding center c_i is calculated;

$(\sigma_1, \dots, \sigma_m)$ – smoothing coefficients (influence parameters, RBF window width parameter), by means of which the radius (sensitivity) of the network is adjusted;

$f_i(x)$ – basis function;

W^l – weight matrix of ordinary linear or sigmoid neurons of the output layer, which determines the output of the network;

$\bar{Y} = (y_1, y_2, \dots, y_j)$ – network output.

At the beginning of the algorithm, the radial-basis level did not contain neurons. They were added to the hidden layer until the sum of the squares of the root mean square (RMS) errors of the network became less than the specified value, or the maximum number of neurons was used. At the next stage, the network forecast was calculated:

- the input vector (with the largest value of the RMS error) was evaluated;
- radial-basis neuron with weights equal to this vector was added;
- weights of a simple linear level were reorganized in such a way as to minimize the RMS error.

Statistics, publicly available on the Eurostat website (Home – Eurostat, 2021), was used for the training of our network, as the forecasting was carried out for the European Union. The initial data in the dynamics of 2020 included:

- employee profits during the Covid-19 pandemic;
- number of unemployed;
- number of people who became ill with Covid-19 (x_1);
- number of people who died as a result of Covid-19 (x_2);
- number of people who recovered after Covid-19 (x_3);
- number of people who were vaccinated (x_4);
- GDP;
- employment of the population;
- distribution of the number of the dismissed employees by industries;
- the number of companies that went bankrupt.

In our network, the neurons of the hidden layer acted on the principle of centering on the elements of the training sample. The weight matrix acted as centers. Vector of smoothing coefficients *($\sigma_1, \ldots, \sigma_m$)*, was used to adjust an area (network sensitivity) around each center, thus the parameters of the hidden layer were adjusted. This approach ensured the relative simplicity of the model with sufficient approximation and prognostic properties, with small "noisy" data samples. The Gaussian function varied in the range from 0 to 1 and determined the yield of the hidden layer:

$$f(x) = e^{\frac{(x-c)^2}{2\sigma^2}} \tag{1}$$

The source layer contained normal linear or sigmoid neurons and by adjusting their weights determined the output of the network.

The properties of such an artificial neural network were completely determined by the radial-basis functions used in the neurons of the hidden layer and formed a certain basis for input image vectors x. In our case, the radial-basis function was a multidimensional function that depended on the distance between the input vector x and its own center c and the width (scale) parameter σ:

$$\Phi(x) = \Phi(\|x - c\|, \sigma) = \Phi(r, \sigma) \tag{2}$$

Thus, each neuron of the latent layer determined the distance between the input vector and its center and performed a nonlinear transformation *$\Phi(r,\sigma)$*. Node centers and synaptic weights were adjusted: $c_i \in R_n$, σ_i, $w_i \in R^l$, i=0,1,2,…,h. For any valid n-dimensional input vector $x = (x_1, x_2, \ldots, x_n)$, where $x \in X \subset R_n$ the network output was determined as follows:

$$y_i = \sum_{k=1}^{m} w_{ik}^{l} f_k \left(dist\left(x, w_k^r\right), \sigma_k \right) \tag{3}$$

where:

$w_{ik}^{l} \in W^{l}$, $i = \overline{1, p}$ – the weights of the linear layer,

$w_k^r \in W^r$ – the centers of radial-basis functions.

Staff turnover, chosen as one of the key indicators of personnel security level, affected the forecasting specifics. Staff turnover is known to be determined by the turnover rate and is calculated as the ratio of the number of laid off employees to the average number of employees, multiplied by 100%. Staff turnover can have an active form, when employees themselves act as initiators of their dismissal, or a passive form, when it is the management who comes up with the idea. Physical and psychological turnover of personnel are also distinguished, with the latter being a time bomb, because the employees do not leave their workplace, but for some reason, cease to work effectively. The decisive factor in this situation is the state of employee's mental health, which is directly affected by external and internal environment. In addition, there is natural and excessive staff turnover. Natural staff turnover is inevitable, whereas excessive turnover poses a serious threat to the personnel security of the enterprise or organization. The allowable average staff turnover limit should be between 5 and 7%. In case its value drops below 5%, a so-called "aging of staff" takes place, which also negatively affects the efficiency level (Wynen *et al.*, 2018).

Given the above, our neural network model was based on the fact that staff losses are calculated by determining staff turnover, which consists of the following elements:

- physical turnover – the number of employees dismissed from the organization (G);
- psychological turnover – the number of employees who do not resign from the organization, but actually cease to bring it profit due to a significant reduction in their productivity caused by psycho-emotional reasons (Q).

During the Covid-19 pandemic, the second component of staff turnover is the most dangerous, as the first one is often even reduced in many industries. The psychological turnover of staff depends on the level of mental health of employees and the level of comfort of the internal environment. Since it can be evaluated only qualitatively, a 100-point scale was used for this purpose:

0 - 20 points – low;
21 - 40 points – below average;
41 - 60 points – average;

61 - 80 points – above average;
81 - 100 – high.

The input parameters for the assessment on the one hand were the factors on which the overall level of mental health depends, namely:

- duration of social and psychological isolation (q_1);
- discrepancies in expectations and reality (q_2);
- work organization quality level reduction (q_3);
- GDP decline (q_4);
- an increase in the number of enterprises and organizations that went bankrupt during the pandemic (q_5) (World Health Organization, 2020).

On the other hand, components of two multiple regression models of the linear type were used, as this approach most accurately describes the impact the Covid-19 pandemic has on staff turnover (Liu and Peng, 2012):

$$У = У_1 + У_2, \tag{4}$$

$$У_1 = a_0 + a_1 \cdot x_1 + a_2 \cdot x_2 \tag{5}$$

where:

a_0 – is a free member;
a_1, a_2, – regression coefficients;
x_1, x_2 – factors influencing the resulting indicator in the model: x_1 – number of employees dismissed by agreement of the parties; x_2 – number of employees dismissed at their own request.

$$У_2 = a_0 + a_1 \cdot z_1 + a_2 \cdot z_2 + a_3 \cdot z_3 + a_4 \cdot z_4, \tag{6}$$

where:

a_0 – is a free member;
a_1, a_2, a_3, a_4 – regression coefficients;
z_1 – the number of those who fell ill;
z_2 – the number of those who recovered;
z_3 – the number of those who died;
z_4 – the number of those who received the vaccine.

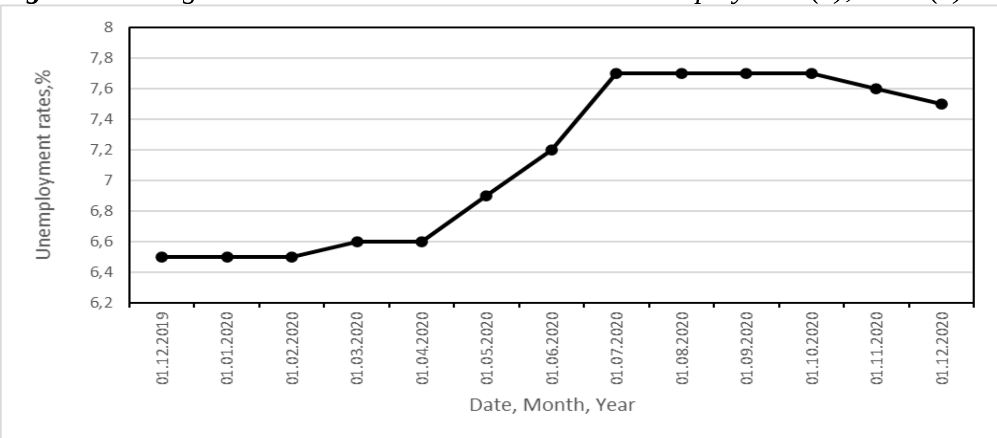
For a correct assessment, it was taken into account that the second term in formula 4 directly affects the psychological turnover of staff. Since the product of the number of employees on labor productivity indirectly characterizes the level of GDP, both the number of employees dismissed by agreement of the parties and the number of those dismissed at their own request were additionally linked to the GDP level as an indicator of quantitative staff losses due to staff turnover (Fahlander and Schwartz, 2007).

At the same time staff turnover as a vector or the arithmetic mean of the flow of admission and dismissal of full-time employees, attributed to their average number was forecasted. After training and testing our neural network, it was found that the error in predicting staff turnover due to the Covid-19 pandemic using the above model is 0.1-0.2%, which confirms the high accuracy of prediction and the possibility of its use for this type of assessment.

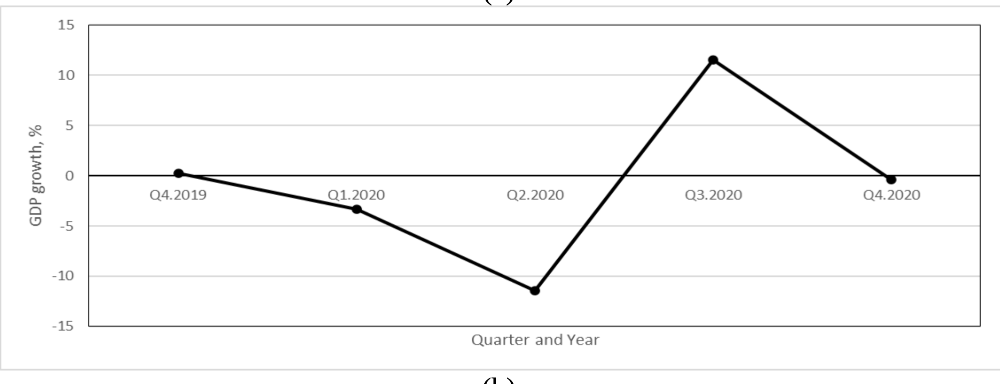
3. Results and Discussion

According to the European Union statistics (27 countries) in December 2020 the number of the unemployed increased by 1.95 million compared to December 2019 (Figure 2a). In the fourth quarter of 2020, the number of unemployed decreased by 0.3% compared to the third quarter of 2020. At the same time, GDP in the fourth quarter of 2020 decreased by 0.7% compared to the third quarter of the same year. In the third quarter, GDP grew by 11.5% compared to the second quarter, although compared with annual indicators, it decreased by 4.3% (Figure 2b).

Figure 2. *Changes in indicators in the EU over time: unemployment (a); GDP (b)*



(a)

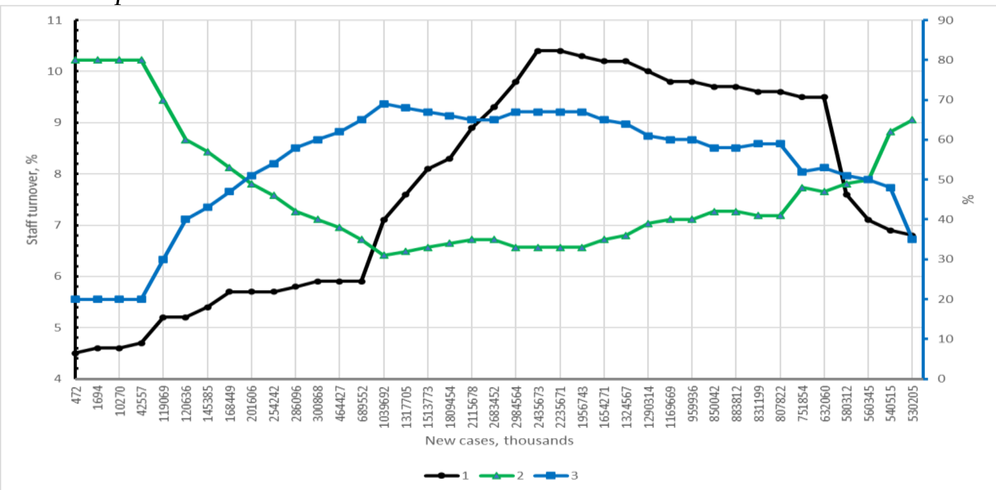


(b)

Source: *Eurostat data.*

In the second quarter GDP declined by record 11.4%. This was the biggest drop since 1995 which pushed the EU economy back for 20 years. The average staff turnover had a fairly wide range of values in different industries. Sales, entertainment and tourism were the most affected. In these areas, staff turnover in the fourth quarter increased to 9.8%, 11.2% and 13.4%, respectively. In the third quarter, the average employment rate in these industries increased by only 0.3% and amounted to 72.4%, despite the summer-autumn period and the beginning of the vaccination. Compared to 2019, the profitability of the tourism sector in the third quarter decreased by 32.3%, and in the fourth quarter it dropped by 48.3%. It should be noted that the psychological component of staff turnover has reached a high level and exceeded the component associated with dismissal by agreement of the parties and at their own request by 15%. This is primarily due to the negative impact of the Covid-19 pandemic on the mental health of people of working age in the EU.

Figure 3. *Outcome indicators for forecasting staff turnover in the EU during the Covid-19 pandemic*



Source: *Own elaboration.*

After forecasting staff turnover, the following results, which are presented in Figure 3, were obtained. Curve 1 presented in black shows the total staff turnover (Y). Curve 2, which appears green, shows the turnover of staff associated with the dismissal of personnel by agreement of the parties and at their own request. Curve 3 shows the psychological turnover of staff that is related to mental health. As a result of forecasting, it is established that with a decrease in the number of patients by 50%, staff turnover rates will not change instantly, but will develop in negative dynamics for another 1 month. This can be explained by the peculiarities of the reaction of the human psyche to irritants. After this period, positive trend is expected. Within six months, while maintaining the positive trend, it will be possible to achieve the optimal personnel loss level of 7%, which will not pose a threat to personnel security of organizations.

In order to achieve a positive trend in staff turnover, more than 70% of the working population of the EU should undergo vaccination. Thus, the required level of personnel security will be achieved according to one of its main key indicators - staff turnover.

4. Conclusions

A conceptual approach to predicting the impact of the Covid-19 pandemic on key indicators of personnel security by means of neural network technologies has been developed. The network architecture is built and its mathematical description is made. The main factors influencing staff turnover as one of the main components of personnel security have been defined. Staff turnover in the EU in 2020 and its dependence on the GDP change value has been analyzed.

The areas most affected by the pandemic have been identified. A forecast has been made for the development of the personnel security situation in case 70% of the EU population is vaccinated. It is established that with a decrease in the number of patients by 50%, staff turnover rates will not change instantly, but will develop in negative dynamics for another 1 month. Therefore, it is important for HR managers to create working conditions favorable for their employees' psychological and mental health.

References:

Brown, W. 2019. In the Ruins of Neoliberalism: The Rise of Antidemocratic Politics in the West (The Wellek Library Lectures). Columbia University Press.

De Winne, S., Marescaux, E., Sels, L., Van Beveren, I., Vanormelingen, S. 2018. The impact of employee turnover and turnover volatility on labor productivity: a flexible non-linear approach. The International Journal of Human Resource Management, 30(21), 3049-3079. https://doi.org/10.1080/09585192.2018.144912.

Fahlander, A., Schwartz, A. 2007. Hidden talent. Boston Consulting Group. Available at: www.bcg.com/impact_expertise/publications/files/Hidden_Talent_July_2007.pdf.

Harel, E., Gomes-Mera, L. 2005. Neoliberalism. Korotkyy oksfordskyy politychnyy slovnyk. – Kyev: Vyd-vo Solomiyi Pavlychko Osnovy, p. 443.

Home-Eurostat. 2021. Available at: https://ec.europa.eu/eurostat.

Isik, F., Ozden, G. 2012. Estimating compaction parameters of fine- and coarse-grained soils by means of artificial neural networks. Environmental Earth Sciences, 69(7), 2287-2297. https://doi.org/10.1007/s12665-012-2057-5.

Kovel, J. 2007. The enemy of nature: The end of capitalism or the end of the world? London: Zed Books.

Krausmann, F., Erb, K.H., Gingrich, S., Haberl, H., Bondeau, A., Gaube, V., Lauk, C., Plutzar, C., Searchinger, T.D. 2013. Global human appropriation of net primary production doubled in the 20th century. Proceedings of the National Academy of Sciences, 110(25), 10324-10329. https://doi.org/10.1073/pnas.1211349110.

Liu, C., Peng, A. 2010. A reinvestigation of contract duration using Quantile Regression for Counts analysis. Economics Letters, 106(3), 184-187. https://doi.org/10.1016/j.econlet.2009.11.015.

Rajasekar, D., Venkateswara Prasad, B. 2017. Employee Job Satisfaction and Intention to Attrition-An Empirical Analysis. International Journal of Mechanical Engineering and Technology, 8(12), 856-861.

Remarks by IMF Managing Director Kristalina Georgieva at the Meeting of the Ministers of Finance and Central Bank Governors of the Gulf Cooperation Council. 2020. Available at: https://www.imf.org/en/News/Articles/2020/10/25/md-remarks-at-the-meeting-of-the-ministers-of-finance-and-central-bank-governors-of-the-gcc.

Shahin, M.A., Jaksa, M.B. 2006. Pullout capacity of small ground anchors by direct cone penetration test methods and neural networks. Canadian Geotechnical Journal, 43(6), 626-637. https://doi.org/10.1139/t06-029.

World Economic Outlook Update: Policy Support and Vaccines Expected to Lift Activity. Available at: https://www.imf.org/en/Publications/WEO/Issues/2021/01/26/2021-world-economic-outlook-update.

World Health Organization. 2020. Physical and mental health key to resilience during COVID-19 pandemic. Available at: http://www. euro.who.int/en/health-topics/health-emergencies/coronaviruscovid-19/statements/statement-physical-and-mental-health-keyto-resilience-during-covid-19-pandemic.

Wynen, J., Van Dooren, W., Mattijs, J., Deschamps, C. 2018. Linking turnover to organizational performance: the role of process conformance. Public Management Review, 21(5), 669-685. https://doi.org/10.1080/14719037.2018.1503704.