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Correlation Analysis of Factors Affecting Firm Performance and Employees Wellbeing: Application of Advanced Machine Learning Analysis

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Abstract: Given the importance of identifying key performance points in organizations, this research intends to determine the most critical intra- and extra-organizational elements in assessing the performance of firms using the European Company Survey (ECS) 2019 framework. The ECS 2019 survey data were used to train an artificial neural network optimized using an imperialist competitive algorithm (ANN-ICA) to forecast business performance and employee wellbeing. In order to assess the correctness of the model, root mean square error (RMSE), mean absolute percentage error (MAPE), mean square error (MSE), correlation coefficient (r), and determination coefficient (R2) have been employed. The mean values of the performance criteria for the impact of internal and external factors on firm performance were 1.06, 0.002, 0.041, 0.9, and 0.83, and the value of the performance metrics for the impact of internal and external factors on employee wellbeing were 0.84, 0.0019, 0.0319, 0.83, and 0.71 (respectively, for MAPE, MSE, RMSE, r, and R2). The great performance of the ANN-ICA model is indicated by low values of MAPE, MSE, and RMSE, as well as high values of r and R2. The outcomes showed that "skills requirements and skill matching" and "employee voice" are the two factors that matter most in enhancing firm performance and wellbeing.

Keywords: organizational performance; machine learning; big data; imperialist competitive algorithm; employee wellbeing; artificial neural networks; firm performance; artificial intelligence; deep learning; data science

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1. Introduction

One of the top goals that today's firms are searching for is a competitive edge. They attempt to achieve this by providing high-quality goods or services. As a result, performance review and quality enhancement seem crucial [1]. Monitoring organizational performance is one of the responsibilities of managers. However, it may be claimed that organizational performance is a wide notion that encompasses both the products and interactions a firm has. Actually, organizational efficiency can be related to the effectiveness of the organization's mission, assignments, and organizational actions, as well as the quality of its outcomes [2]. One of the challenges that the business and academic sectors have given a significant deal of interest to is organizational performance evaluation [3]. In order to achieve the objective of the business with the highest level of performance and to serve the needs of the workforce, there is a need to employ performance evaluation using the effective instruments and methods of human resource management. An efficient evaluation system that also makes use of its findings is necessary for the organization's growth and the quality of its personnel. Naturally, by enhancing employee effectiveness, formulating and having a performance evaluation process in place can help companies achieve their objectives [3].

The literature contains evidence that one of the elements impacting the performance of firms is management factors. The organizational ideals and mission are defined by managers who also make them accessible, develop the values necessary for long-term success, and put those values into practice through proper action and behavior. These elements may have a direct or indirect impact on how well a company performs and how it conducts business [4]. Another element whose influence on businesses' success has been researched and verified is human resources [5,6]. Making people productive in the production and service sectors is crucial for joining international markets and building an economy in the current period of intense market rivalry. Quality, affordability, and speed are the three competitive advantages. In order to improve their innovation culture, several firms opt for a command and control culture [7]. Another factor that significantly affects how well businesses succeed is organizational structure. Synchronizing organizational performance with employee welfare is crucial for improving organizational performance. In recent years, machine learning (ML) techniques have provided valuable tools for evaluating systems [8,9], modeling proper frameworks [10,11] and increasing system accuracy [12]. ML-based techniques can successfully link the dependent and independent variables to provide a practical mapping of a system. Fredström et al. (2022) suggested that using ML techniques improves business success, and companies should communicate using terms connected to AI, particularly when discussing innovation and teamwork [13]. Shaaban et al. (2022) employed association rule algorithms, Apriori algorithm, and chi-square automatic interaction detection analysis tree to enhance business performance. This enhancement also provides considerable wellbeing [14]. Ahmed et al. (2022) employed ML techniques for boosting business performance [15]. As is clear from the literature, ML provides a promising output for analyzing firm performance and employee wellbeing. In the present study, an advanced ML was employed to provide a conceptual framework of firm performance and employee wellbeing. In the following, the provided framework was employed to identify the most effective parameters for firm performance and employee wellbeing. The ECS (2019) conceptual framework is used to assess firm performance [16]. The two outputs of this model are the effectiveness of the company and the happiness of the employees. Two levels of variables, organizational features and the external environment, are said to have an impact on these outcomes. Organizational features include job organization, skills availability and skill development, and employee voice, according to Eurofound and Cedefop (2020) [17], Valeyre et al. (2009) [18], and Haapakorpi and Alasoini (2018) [19]. Accordingly, the present study has three main layers. The first layer presents the characteristics of the dataset, the second layer presents the modeling phase, and the last layer is a description of the results and findings for proper policy making in the field.

2. Materials and Methods

2.1. Dataset Description

The dataset was prepared according to the 2019 European Company Survey (ECS). In the 2019 ECS, 3,073 employee representatives and 21,869 management representatives from 27 EU Member States participated in an interview-based representative sample survey [17]. The data must first be unified since various data types utilize distinct units of measurement before being subjected to quantitative analysis. For instance, the ESC model assesses "work organization" using the two variables "collaboration and outsourcing" and "job complexity and autonomy". There are eight questions that have been created to gauge complexity and autonomy, and each question has a yes/no response option. The respondent must select one of the two alternatives in order to respond to two of the eight questions. The work of quantitative data analysis is made challenging by the discrepancy in the units of measurement of the inquiries. As a result, the questions were originally changed and combined, and each was rewritten such that the responses may be either zeros or ones. For instance, for yes or no questions and questions where the respondent had to select an alternative, one was provided for a yes response and zero for a no response. The option that was not chosen received a score of 0, whereas the chosen option received a score of 1.

Figure 1 presents the variables employed in the study and their definitions. According to Table 1, each area contains factors that have been extracted from the questionary. Employee wellbeing and firm performance are two dependent factors. Work organization was evaluated using collaboration and outsourcing and job complexity and autonomy. Skills use and skills strategies was evaluated using "skills requirements and skills match" and "training and skill development". Employee voice was evaluated using "direct employee participation" and "indirect employee participation". The external environment was evaluated using "innovation", "digitalization", and "product market strategy". All these parameters had an effect on the "employee wellbeing" and "firm performance" as the two outputs of the system.

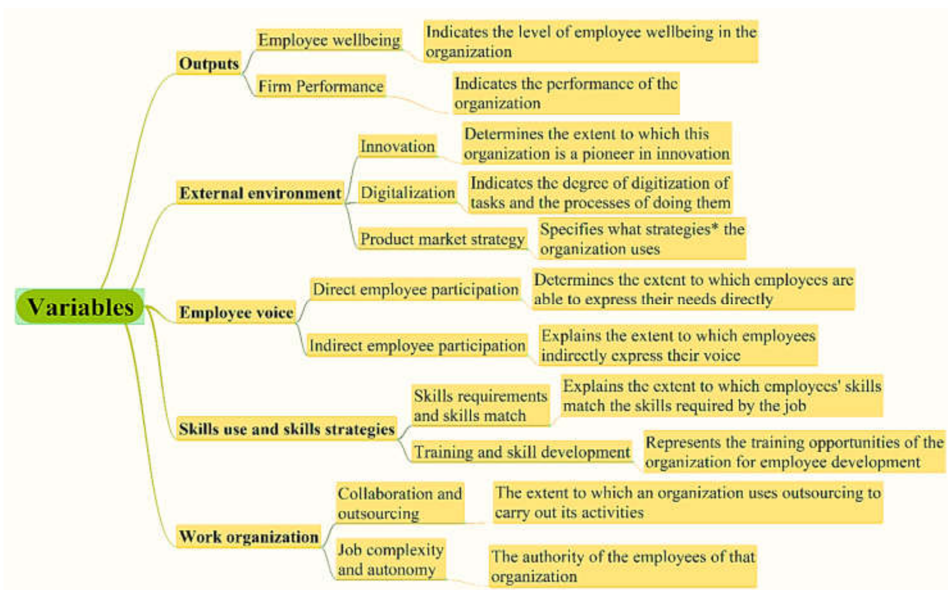


Figure 1. The explanation of the variables. The stared strategies are listed related to product market guideline.

Table 1. Training MAPE for the effect of work organization on outputs.

Order	Neuron Arrangements for Hidden Layer	No. of Countries	No. of ITERATIONS	Prodvol_68	Profit_69	Profplan_70	Chempfut_71	Sickleave_59	Lowmot_60	Retainemp_62	Qwprel_63
1	**20-10**	**100**	1000	7.314	6.706	5.304	6.903	5.801	5.756	7.423	8.123
2	**20-10**	**200**	1000	6.001	5.804	5.112	6.209	5.111	5.569	7.057	7.912
3	**20-10**	**300**	1000	5.905	5.586	4.920	6.017	5.765	5.554	6.929	7.178
4	**20-10-5**	**100**	1000	5.271	5.002	5.000	5.343	5.887	5.021	6.045	6.213
5	**20-10-5**	**200**	1000	4.364	4.632	4.323	5.009	5.521	4.982	5.944	5.965
6	**20-10-5**	**300**	1000	4.133	4.895	3.903	4.522	5.108	4.020	5.420	5.651
7	**30-20**	**100**	1000	4.199	4.555	3.429	4.043	4.822	3.858	5.010	5.400
8	**30-20**	**200**	1000	3.906	4.004	3.005	3.788	4.011	3.201	4.831	5.187
9	**30-20**	**300**	1000	3.819	3.777	2.487	3.115	3.333	2.871	4.338	4.876
10	**30-20-10**	**100**	1000	3.542	3.008	1.999	2.911	2.024	2.006	3.999	4.077
11	**30-20-10**	**200**	1000	2.788	2.001	1.461	2.700	1.211	1.458	3.503	3.522
12	***30-20-10***	***300***	*1000*	*2.033*	*1.366*	*1.103*	*2.231*	*0.899*	*0.700*	*3.114*	*2.900*

2.2. Machine Learning Method

The present study developed an advanced multi-layered perceptron (MLP) integrated with the imperialist competitive algorithm (ICA) (called ANN-ICA) [20] to analyze the factors affecting firm performance and employee wellbeing. MLP is one of the most popular multilayer feeder networks [21,22]. This network processes existing data using activation functions in tandem layers. In this network, the input signals in each step by forwarding transmit the error signal for each node in the output layer [23,24]. The resulting error rate moves backward, and the weights and biases of the network change. Several activation functions are applied to the input to produce the neuron output. The outputs are then transmitted as input to the neurons in the next layer. Sigmoid transfer functions may be used when dealing with nonlinear situations.

Atashpaz-Gargari and Lucas [25] developed the imperialist competitive algorithm (ICA) as a solution for optimization problems. A random population solution initiates ICA. In ICA, the individuals are referred to as countries. The best solution is for the countries with the maximum power to be identified as imperialists. Figure 2 presents the main algorithm for the ICA optimization.

The capabilities of the MLP network can be improved with meta-heuristic algorithms such as ICA [26]. These algorithms can replace the learning algorithm in the MLP network and adjust the weight and bias values to reduce the network output error. In this study, a combination of the MLP network with ICA (called MLP-ICA) investigated the correlation analysis of the factors affecting firm performance and employee wellbeing. The network was implemented based on the study of different treatments in terms of the number of hidden layers, the number of neurons in each layer, and the number of populations in a fixed number of iterations. This method was performed in the network training phase, and the analyses were performed using different indices to find the best network configuration. The results of this step are shown in Tables 1–4 for the various outputs based on mean absolute percentage error (MAPE). Equations (1)–(4) present the evaluation metrics for comparing the model's output with the target values [27–31].

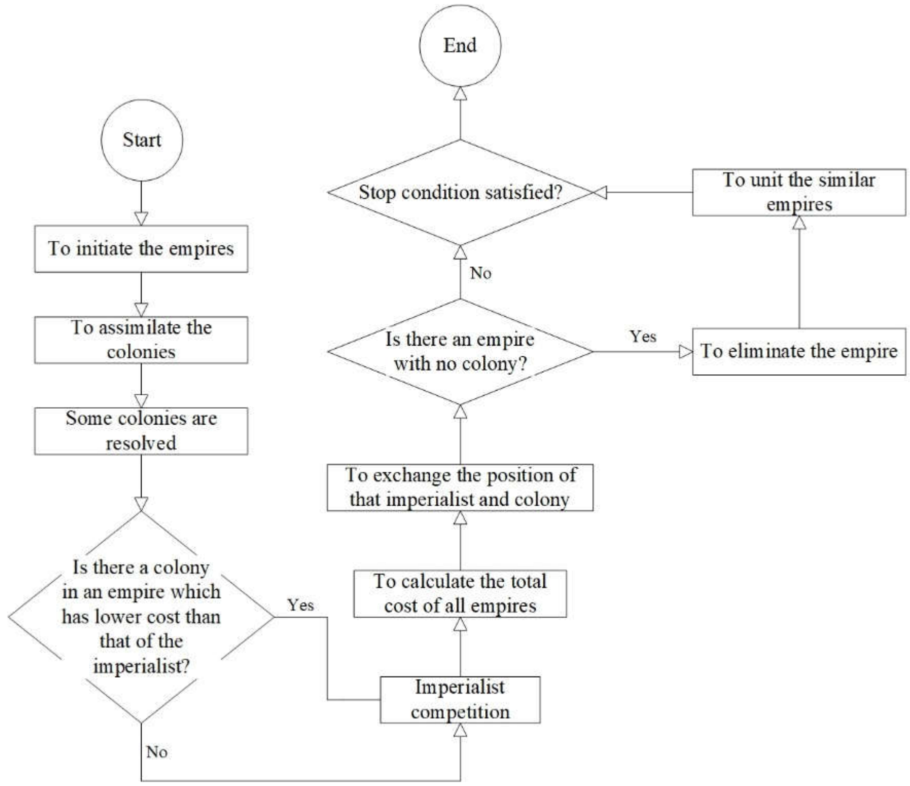


Figure 2. A schematic representation of the ICA algorithm.

$$\text{Mean square error (MSE)} = \frac{1}{t\times o}\sum_{i=1}^{o}\sum_{j=1}^{t}(T_{ij}-O_{ij})^2 \quad (1)$$

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{1}{t\times o}\sum_{i=1}^{o}\sum_{j=1}^{t}(T_{ij}-O_{ij})^2} \quad (2)$$

$$\text{Correlation coefficient (r)} = \sqrt{\frac{\sum_{i=1}^{n}[(O_i-\bar{O})(T_i-\bar{T})]}{\sum_{i=1}^{n}[(O_i-\bar{O})^2\sum_{i=1}^{n}(T_i-\bar{T})^2]}} \quad (3)$$

$$\text{Mean absolute percentage error (MAPE)} = 100\times\frac{1}{o\times t}\sum_{i=1}^{o}\sum_{j=1}^{t}\left|\frac{T_{ij}-O_{ij}}{T_{ij}}\right| \quad (4)$$

$$\text{Determination coefficient (R2)} = \frac{\sum_{i=1}^{n}[(O_i-\bar{O})(T_i-\bar{T})]}{\sum_{i=1}^{n}[(O_i-\bar{O})^2\sum_{i=1}^{n}(T_i-\bar{T})^2]} \quad (5)$$

where O refers to the output values, T refers to the target values, o refers to the number of output values, t refers to the number of target values, and n refers to the number of data.

Table 2. Training MAPE for the effect of skill requirements on outputs.

Order	**Neuron Arrangements for Hidden Layer**	**No. of Countries**	**No. of Iterations**	**Prodvol_68**	**Profit_69**	**Profplan_70**	**Chempfut_71**	**Sickleave_59**	**Lowmot_60**	**Retainemp_62**	**Qwprel_63**
1	**20-10**	**100**	1000	7.113	0.899	4.161	2.100	1.422	4.198	0.0500	0.903
2	**20-10**	**200**	1000	6.001	0.702	3.604	1.912	1.310	3.698	0.048	0.803
3	**20-10**	**300**	1000	5.434	0.732	3.169	1.808	1.278	3.121	0.031	0.800

4	**20-10-5**	**100**	1000	5.005	0.693	2.234	1.721	1.162	2.891	0.020	0.731
5	**20-10-5**	**200**	1000	4.777	0.613	1.906	1.600	1.001	2.400	0.008	0.605
6	**20-10-5**	**300**	1000	4.100	0.501	1.333	1.449	0.912	2.005	0.006	0.500
7	**30-20**	**100**	1000	3.356	0.412	1.125	1.228	0.900	1.977	0.004	0.389
8	**30-20**	**200**	1000	2.988	0.290	0.996	0.991	0.787	1.822	0.003	0.201
9	**30-20**	**300**	1000	2.401	0.056	0.721	0.620	0.422	1.701	0.003	0.142
10	**30-20-10**	**100**	1000	1.889	0.014	0.506	0.399	0.211	1.498	0.002	0.099
11	**30-20-10**	**200**	1000	0.987	0.0009	0.422	0.100	0.098	1.032	0.001	0.049
12	***30-20-10***	***300***	*1000*	*0.301*	*0.0005*	*0.297*	*0.0403*	*0.014*	*0.432*	*0.0000*	*0.013*

Table 3. Training MAPE for the effect of employee voice on outputs.

Order	**Neuron Arrangements for Hidden Layer**	**No. of Countries**	**No. of Iterations**	**Prodvol_68**	**Profit_69**	**Profplan_70**	**Chempfut_71**	**Sickleave_59**	**Lowmot_60**	**Retainemp_62**	**Qwprel_63**
1	**20-10**	**100**	1000	5.014	6.891	2.093	3.618	2.948	2.094	3.577	2.051
2	**20-10**	**200**	1000	4.194	5.792	1.999	3.321	2.431	1.901	3.113	1.901
3	**20-10**	**300**	1000	3.900	5.299	1.891	2.965	2.131	1.872	2.976	1.878
4	**20-10-5**	**100**	1000	3.564	5.014	1.700	2.432	1.990	1.789	2.667	1.750
5	**20-10-5**	**200**	1000	3.109	4.842	1.509	2.006	1.776	1.609	2.067	1.450
6	**20-10-5**	**300**	1000	2.942	4.511	1.400	1.891	1.540	1.430	1.645	1.251
7	**30-20**	**100**	1000	2.777	3.888	1.294	1.603	1.345	1.202	1.236	1.051
8	**30-20**	**200**	1000	2.001	3.001	1.010	1.590	1.223	1.029	1.069	0.905
9	**30-20**	**300**	1000	1.666	2.118	0.822	1.333	1.005	0.999	0.907	0.850
10	**30-20-10**	**100**	1000	1.213	1.542	0.555	1.003	0.899	0.621	0.700	0.502
11	**30-20-10**	**200**	1000	0.801	1.002	0.282	0.872	0.567	0.328	0.699	0.200
12	***30-20-10***	***300***	*1000*	*0.488*	*0.719*	*0.099*	*0.444*	*0.302*	*0.121*	*0.586*	*0.099*

Table 4. Training MAPE for the effect of the external environment on outputs.

Order	**Neuron Arrangements for Hidden Layer**	**No. of Countries**	**No. of Iterations**	**Prodvol_68**	**Profit_69**	**Profplan_70**	**Chempfut_71**	**Sickleave_59**	**Lowmot_60**	**Retainemp_62**	**Qwprel_63**
1	**20-10**	**100**	1000	7.5194	5.9298	5.4228	4.9581	5.268	5.142	7.074	6.141
2	**20-10**	**200**	1000	6.944	5.268	5.005	4.101	4.811	4.992	6.714	5.800
3	**20-10**	**300**	1000	6.532	4.999	4.898	3.911	4.333	4.215	6.001	5.150
4	**20-10-5**	**100**	1000	6.001	4.708	4.451	3.526	4.089	4.000	5.704	4.845
5	**20-10-5**	**200**	1000	5.823	4.277	4.021	3.051	3.698	3.482	5.048	4.101
6	**20-10-5**	**300**	1000	5.104	3.810	3.709	2.508	3.064	3.100	4.571	3.811
7	**30-20**	**100**	1000	4.601	3.021	3.202	1.968	2.939	2.777	4.061	3.112
8	**30-20**	**200**	1000	3.904	2.987	2.658	1.501	2.282	2.452	3.379	2.642
9	**30-20**	**300**	1000	3.101	2.892	2.202	1.331	2.008	2.012	3.005	2.465
10	**30-20-10**	**100**	1000	2.400	2.598	2.002	1.111	1.841	1.723	2.893	2.001
11	**30-20-10**	**200**	1000	2.000	2.220	1.777	1.032	1.570	1.404	2.500	1.555
12	***30-20-10***	***300***	*1000*	*1.999*	*1.872*	*1.383*	*0.876*	*1.380*	*1.130*	*2.170*	*1.132*

Based on the results presented in Tables 1–4, increasing the number of hidden layers, the number of neurons, and the number of countries increased the model's accuracy. Model No. 12 was selected as the best model for the prediction of firm performance and employee wellbeing with the lowest MAPE. The best architecture was obtained to be 11-30-20-10-2. It should be noted that the modeling and analysis were performed using MATLAB software (version R2022a, The MathWorks, Inc. New York, NY, USA) on hardware consisting of an Intel® Core™ i7-8557U CPU @ 1.70 GHz and 16 GB RAM in the presence of the 70% of the dataset as the training dataset and 30% of the dataset as the testing dataset. The increasing number of layers and neurons and the number of countries require more processing time and power due to the huge number of datasets. Figure 3 also shows the implementation algorithm of the desired network.

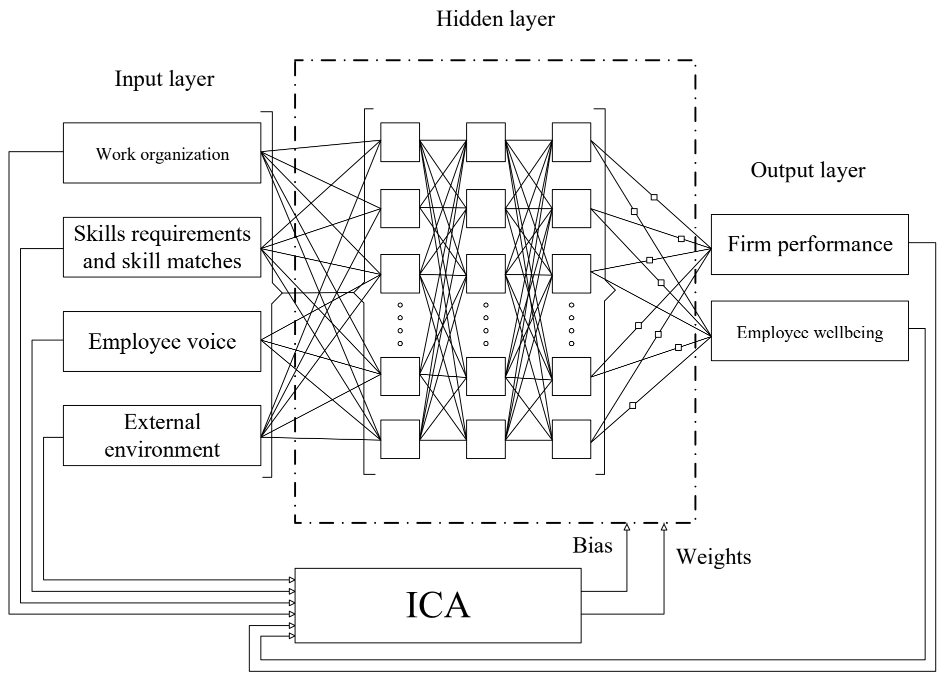


Figure 3. The architecture of the proposed method.

According to Figure 3, ICA adjusts the bias and weights using the relations of input and output values and provides a training algorithm for the MLP method. Work organization, skills requirements and skill matches, employee voice, and external environment are considered as the independent variables, and firm performance and employee wellbeing are considered as the dependent variables. The next step presents the results and discussion section.

3. Results

This section has two main categories. The first phase presents the analytical results for the nature of the dataset and the second phase provides the modeling results.

3.1. Mean Value Analysis

This section presents the mean value analysis for the target values. This analysis provides a simple and accurate sight of the dataset's range, min, max, and average values for better discussion (Table 5).

Table 5. Descriptive statistics for the effect of results on the dataset.

Parameter	Minimum	Maximum	Mean	Std. Deviation
sickleave_59	1	2	1.745542	0.435606
lowmot_60	1	2	1.78235	0.412695
retainemp_62	1	2	1.3123	0.463484
qwprel_63	1	2	1.859625	0.347415
prodvol_68	1	2	1.501143	0.500056
profit_69	1	2	1.714906	0.451511
profplan_70	1	2	1.807727	0.394131
chempfut_71	1	2	1.322359	0.467433

3.2. Modeling Results

This section presents the testing phase modeling results. Accordingly, the highest correlation can refer to the highest impact of that parameter on the output value. Tables 6–13 refer to the testing results for work organization, skills requirements and skill matches, employee voice, and external environment, and their impact on the firm performance, and employee wellbeing, respectively. Each table also presents the average values for better justification.

Table 6. Testing results for the effect of work organization on firm performance.

Work Organization	Prodvol_68	Profit_69	Profplan_70	Chempfut_71	Average
MAPE	2.217	1.546	1.230	2.857	1.962
MSE	0.004	0.003	0.003	0.004	0.004
RMSE	0.064	0.058	0.057	0.063	0.060
R	0.893	0.876	0.831	0.852	0.863
R2	0.797	0.767	0.691	0.727	0.745

Table 7. Testing results for the effect of work organization on employee wellbeing.

Work Organization	Sickleave_59	Lowmot_60	Retainemp_62	Qwprel_63	Average
MAPE	0.727	0.842	3.209	1.045	1.456
MSE	0.002	0.001	0.006	0.002	0.003
RMSE	0.044	0.036	0.078	0.047	0.051
R	0.904	0.797	0.682	0.821	0.801
R2	0.818	0.635	0.464	0.673	0.648

Table 8. Testing results for the effect of skills requirements and skill matches on firm performance.

Skills Requirements and Skill Matches	Prodvol_68	Profit_69	Profplan_70	Chempfut_71	Average
MAPE	0.0084	0.7622	0.0000	0.0293	0.2000
MSE	0.0001	0.0010	0.0001	0.0001	0.0002
RMSE	0.0004	0.0310	0.0001	0.0038	0.0088
R	0.9996	0.9426	0.9997	0.9992	0.9854
R2	0.9999	0.8885	0.9999	0.9983	0.9717

Table 9. Testing results for the effect of skills requirements and skill matches on employee well-being.

Skills Requirements and Skill Matches	Sickleave_59	Lowmot_60	Retainemp_62	Qwprel_63	Average
MAPE	0.3338	0.0002	0.4586	0.0330	0.2064
MSE	0.0012	0.0001	0.0023	0.0004	0.0010
RMSE	0.0351	0.0001	0.0482	0.0209	0.0260
R	0.9183	0.9996	0.7196	0.9531	0.8978
R2	0.8433	0.9999	0.5178	0.9085	0.8174

Table 10. Testing results for the effect of employee voice on firm performance.

Employee Voice	Prodvol_68	Profit_69	Profplan_70	Chempfut_71	Average
MAPE	0.5149	0.8209	0.0990	0.1306	0.3914
MSE	0.0008	0.0013	0.0000	0.0001	0.0005
RMSE	0.0284	0.0356	0.0046	0.0071	0.0189
R	0.9708	0.9229	0.9983	0.9971	0.9723
R2	0.9425	0.8517	0.9967	0.9942	0.9462

Table 11. Testing results for the effect of employee voice on employee wellbeing.

Employee Voice	Sickleave_59	Lowmot_60	Retainemp_62	Qwprel_63	Average
MAPE	0.3384	0.2290	0.6067	0.0500	0.3060
MSE	0.0003	0.0005	0.0010	0.0003	0.0005
RMSE	0.0185	0.0219	0.0316	0.0179	0.0225
R	0.9775	0.9205	0.8755	0.9649	0.9346
R2	0.9556	0.8474	0.7665	0.9311	0.8752

Table 12. Testing results for the effect of the external environment on firm performance.

External Environment	Prodvol_68	Profit_69	profplan_70	Chempfut_71	Average
MAPE	2.5194	1.9298	1.4228	0.9581	1.7075
MSE	0.0081	0.0130	0.0031	0.0027	0.0067
RMSE	0.0898	0.1139	0.0560	0.0516	0.0778
R	0.8296	0.6417	0.8629	0.9206	0.8137
R2	0.6883	0.4118	0.7447	0.8475	0.6731

Table 13. Testing results for the effect of the external environment on employee wellbeing.

External Environment	Sickleave_59	Lowmot_60	Retainemp_62	Qwprel_63	Average
MAPE	1.268	1.142	2.074	1.141	1.4062
MSE	0.004	0.004	0.003	0.003	0.0033
RMSE	0.061	0.061	0.052	0.053	0.0569
R	0.787	0.481	0.845	0.688	0.7003
R2	0.619	0.232	0.714	0.474	0.5096

Figures 4–11 present the plot diagrams for the testing phase separately for firm performance and employee wellbeing. These figures evaluate the linearity of target values against the output values. These figures also present the trendline, including the determination coefficient, for better analysis.

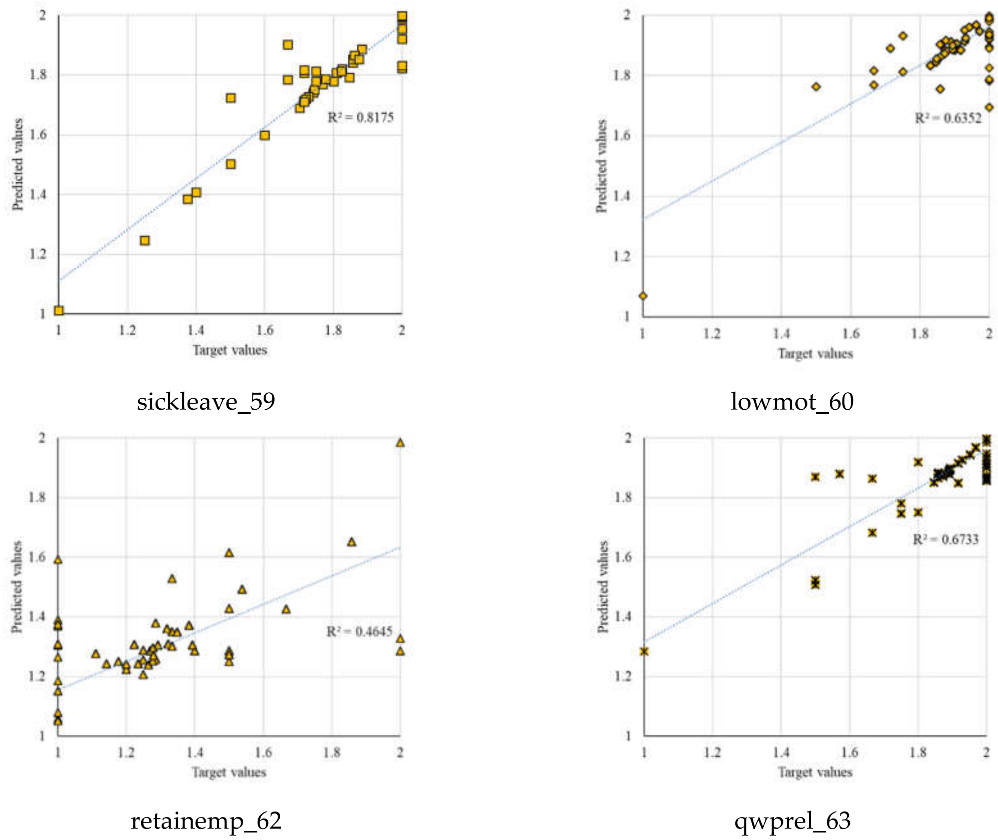


Figure 4. Plot diagrams for the effects of work organization on output values of employee wellbeing.

According to Figure 4, the mean value of linearity for predicting employee wellbeing using a working organization is about 64%. Figure 5 presents the effect of working organization on firm performance. As is clear from Figure 5, the mean value of linearity for predicting firm performance using a working organization is about 74%, which is about 10% higher than that for predicting employee wellbeing. This trend describes that the effect of work organization-related factors on firm performance is about 15% higher than that of the effect of work organization-related factors on employee wellbeing.

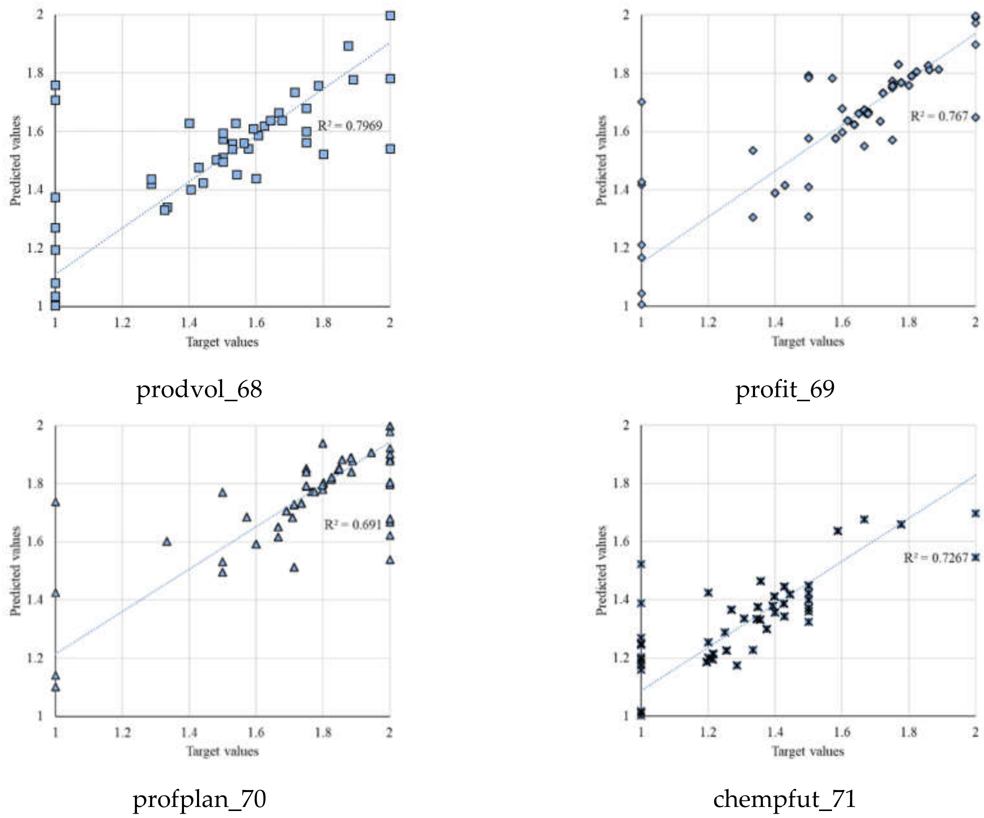


Figure 5. Plot diagrams for the effects of work organization on output values of firm performance.

The mean value of linearity for forecasting employee wellbeing using skills requirements and skill matches-related factors is approximately 86%, as shown in Figure 6. The impact of skills requirements and skill matches-related factors on firm performance is shown in Figure 7.

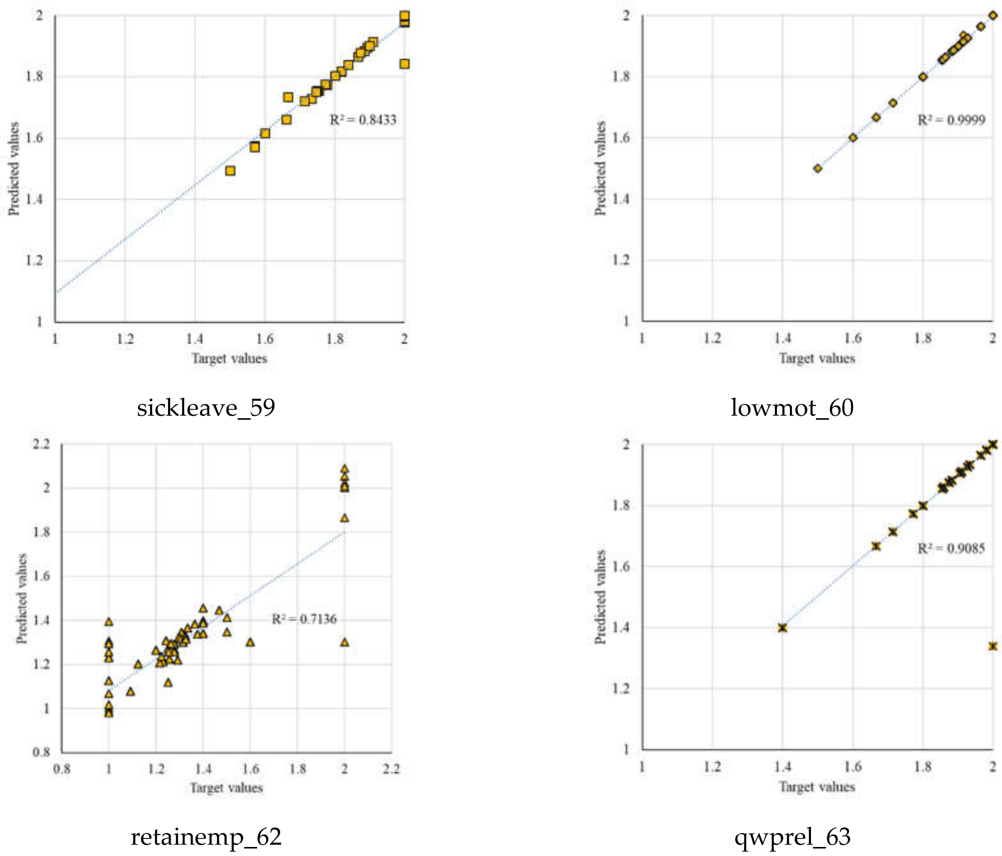
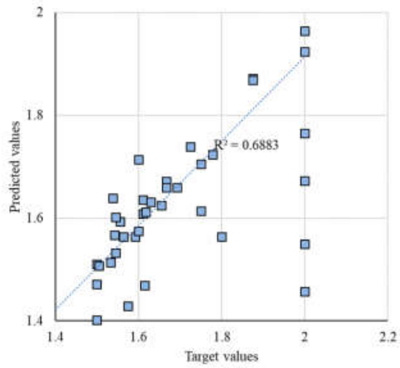
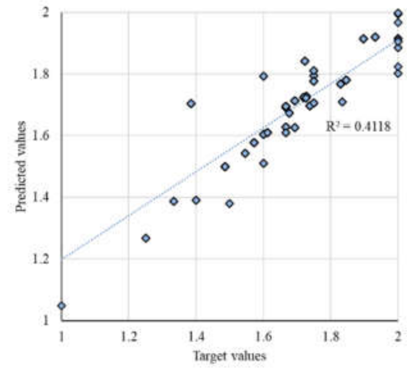


Figure 6. Plot diagrams for the effects of skills requirements and skill matches on output values of employee wellbeing.

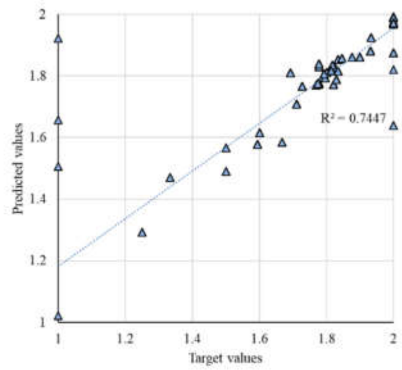
The mean value of linearity for predicting firm performance using skills requirements and skill matches is approximately 67%, which is about 19% lower than that for predicting employee wellbeing. According to this tendency, the impact of skills requirements and skill matches-related characteristics on firm performance is around 22% lower than the impact of those same factors on employee wellbeing.



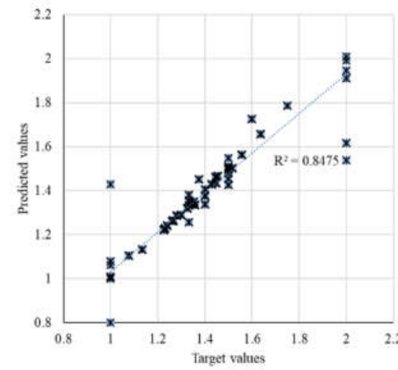
prodvol_68



profit_69



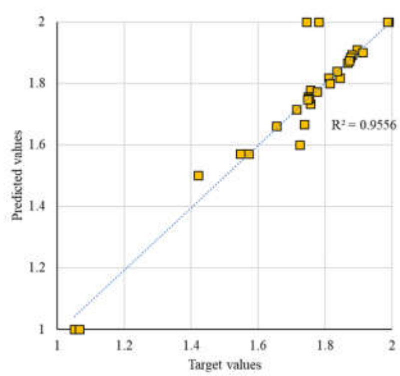
profplan_70



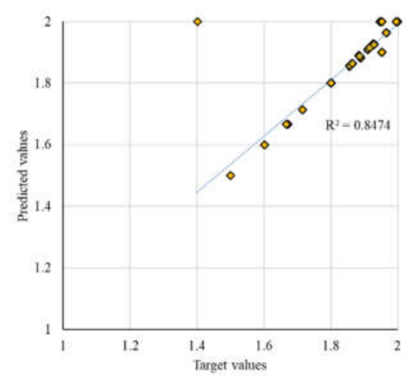
chempfut_71

Figure 7. Plot diagrams for the effects of skills requirements and skill matches on output values of firm performance.

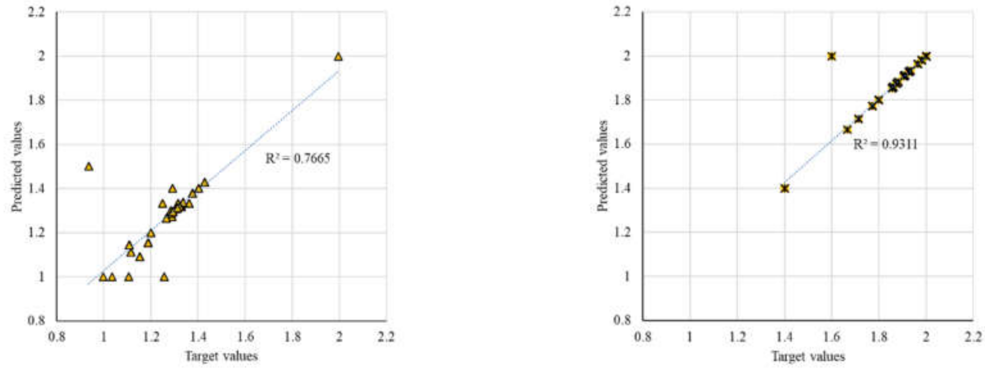
According to characteristics connected to employee voice, the mean value of linearity for predicting employee wellbeing is roughly 87%, as shown in Figure 8. Figure 9 illustrates how factors related to employee voice affect firm performance.



sickleave_59



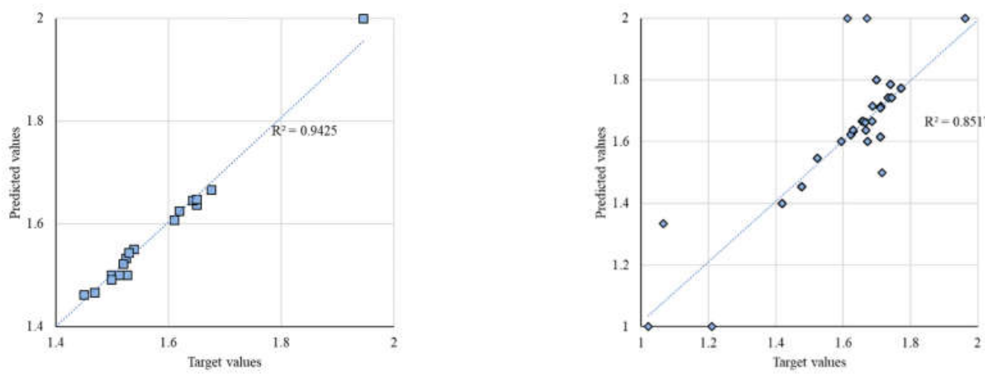
lowmot_60



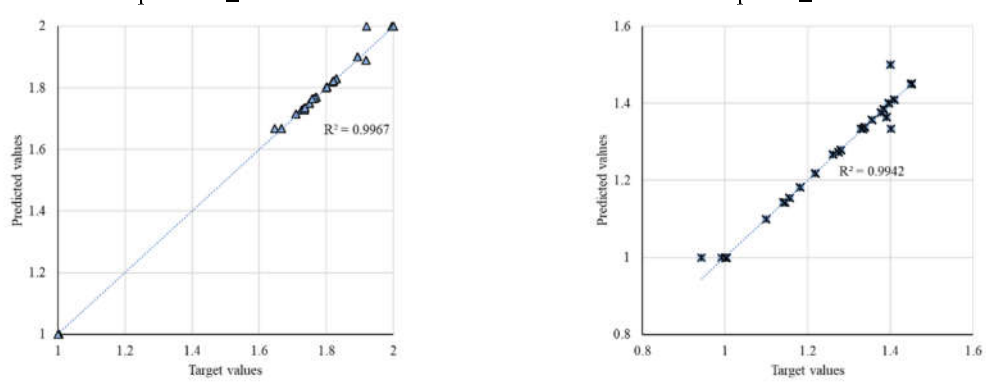
retainemp_62 qwprel_63

Figure 8. Plot diagrams for the effects of employee voice on output values of employee wellbeing.

Figure 9 shows that the mean value of linearity for forecasting firm performance based on employee voice is around 94%, which is about 7% higher than that for predicting employee wellbeing. This pattern indicates that the influence of employee voice-related features on firm performance is around 8% higher than the influence of the same qualities on employee wellbeing.



prodvol_68 profit_69



profplan_70 chempfut_71

Figure 9. Plot diagrams for the effects of employee voice on output values of firm performance.

Figures 10 and 11 present the effects of the external environment-related factors on output values of employee wellbeing and firm performance, respectively. Figure 10 illustrates the mean value of linearity for forecasting employee wellbeing based on factors related to the external environment, which is around 52%. The impact of parameters connected to the external environment on firm performance is seen in Figure 11.

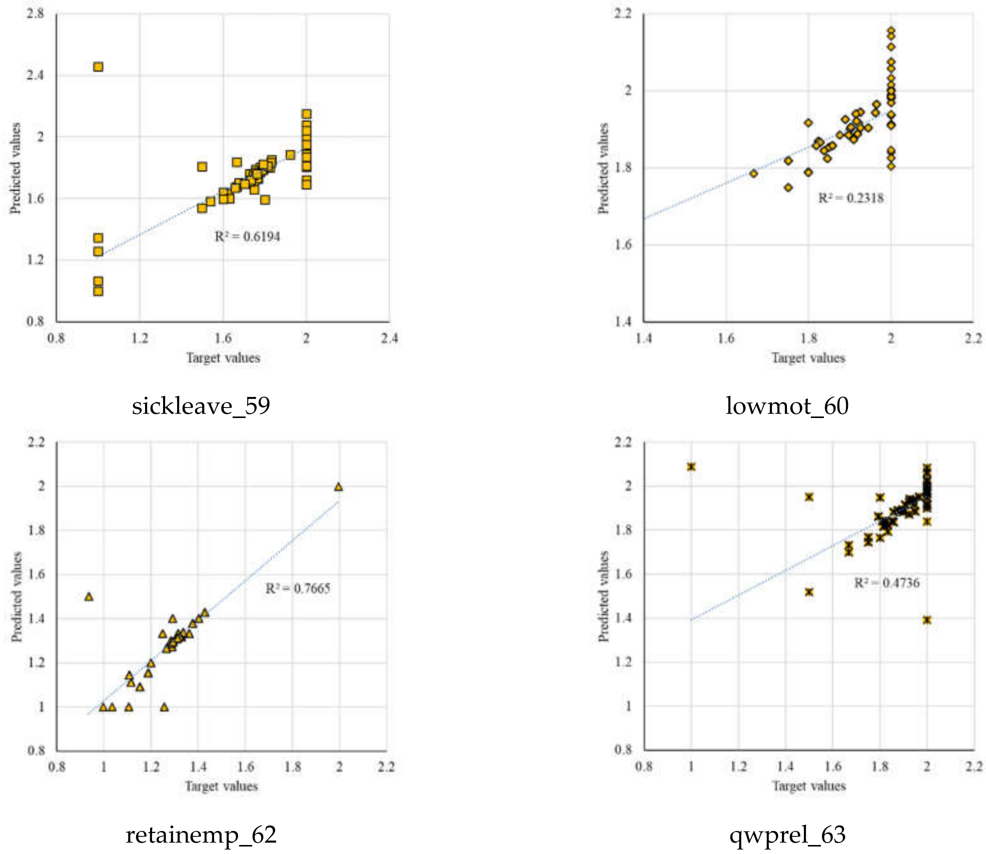
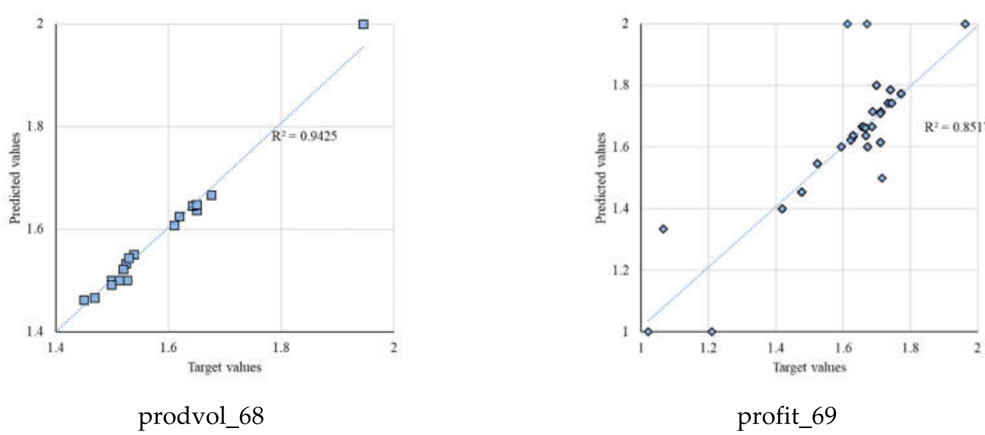
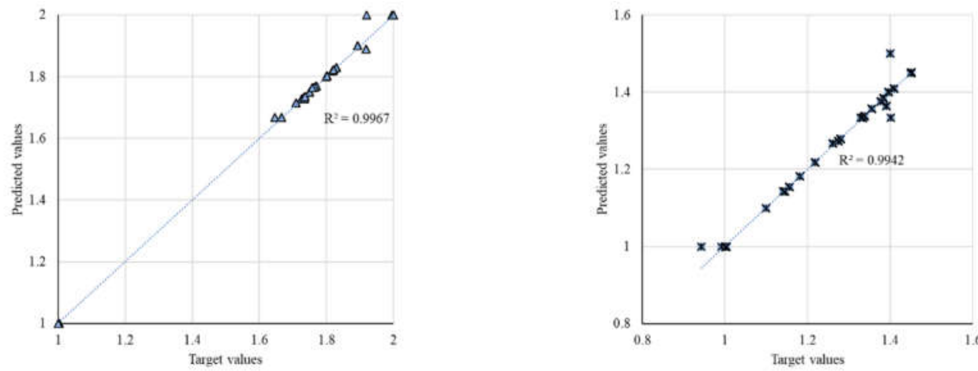


Figure 10. Plot diagrams for the effects of the external environment on output values of employee wellbeing.

Figure 11 demonstrates that the average linearity for predicting firm performance using the external environment is around 94%, which is roughly 42% higher than that for predicting employee wellbeing. This trend suggests that the impact of external environment-related characteristics on firm performance is approximately 80% greater than the impact of the same characteristics on employee wellbeing.

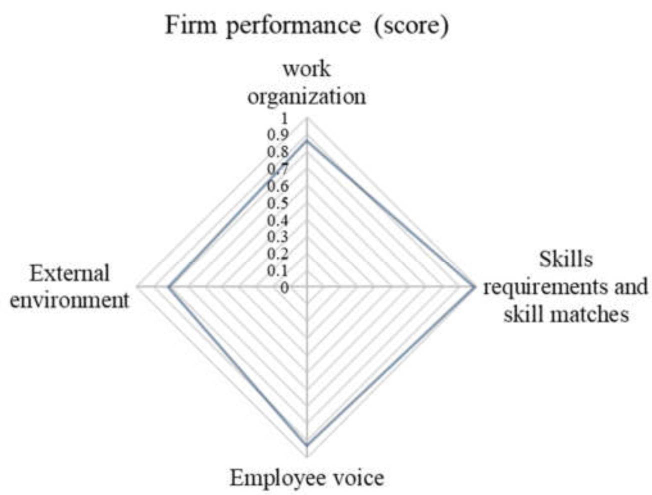




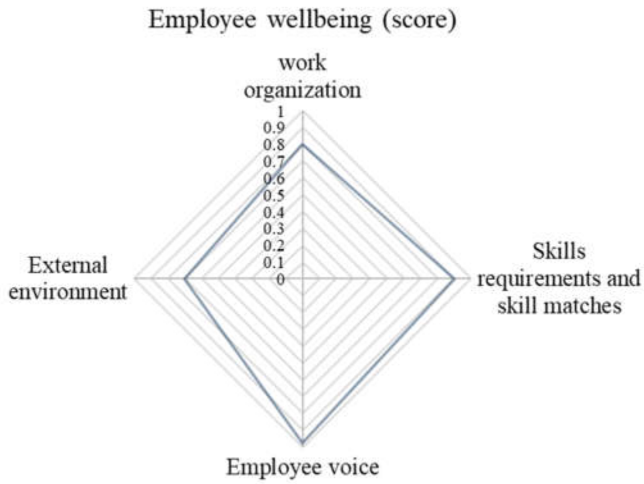
profplan_70 chempfut_71

Figure 11. Plot diagrams for the effects of the external environment on output values of firm performance.

Figure 12 presents the main findings from the previous sections for describing the effects of the independent parameters on the output values. As is clear from Figure 8, skill requirements and skill matches have the highest correlation with firm performance. However, in the case of employee wellbeing, the highest correlation refers to the employee voice. It can be mentioned that skill requirements and skill matches and employee voice have the highest impact on firm performance and employee wellbeing, respectively.



Firm performance



Employee wellbeing

Figure 12. Analyzing the effects of independent parameters on output values.

4. Conclusions

This study was employed for the evaluation of the firm performance and employee wellbeing parameters using the ANN-ICA technique. Outputs of the models have been compared using evaluation criteria with the target values. In the second phase, the effect of each independent category was considered compared to the output values to find the most effective variables. According to the findings, the model architecture of 11-30-20-10-2 (11 inputs interconnected with 30 neurons in the first hidden layer, 20 neurons in the second hidden layer, 10 neurons in the third hidden layer, and 2 outputs) was selected as the best model for the prediction of the firm performance and employee wellbeing with the lowest MAPE. According to the findings, it can be mentioned that, when predicting company success (firm performance) using working organizations, the mean value of linearity was around 74%, which is about 10% higher than that for predicting employee wellbeing. This pattern showed that the impact of work organization-related characteristics on firm performance was around 15% greater than the impact of these same factors on employee wellbeing. The mean value of linearity, on the other hand, was around 67% for forecasting firm performance using skill needs and skill matches, which was roughly 19% lower than that for predicting employee wellbeing. This tendency indicates that the influence of the qualities linked to the skills needed and skill matching on firm performance was approximately 22% less than the impact of the same characteristics on employee wellbeing. Additionally, based on employee feedback, the mean linearity for predicting firm performance was about 94%, which was around 7% higher than that for predicting employee wellbeing. This trend showed that the impact of characteristics linked to employee voice on firm performance was around 8% more than the impact of the same characteristics on employee wellbeing. Furthermore, the average linearity for forecasting firm performance using the external environment was about 94%, which was roughly 42% higher than that for forecasting employee wellbeing. According to this pattern, the influence of factors connected to the external environment on a company's success was almost 80% bigger than its influence on employee wellbeing. It would be exciting to use this method (ANN-ICA) to identify the cross-country differences covering EU-27 countries involved in the ECS 2019 survey. It would be exciting to locate country group differences (e.g., Nordic countries, continental countries, Mediterranean countries, etc.).

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