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Modeling Organizational Performance with Machine Learning

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Abstract: Identifying the performance factors of organizations is of utmost importance for labor studies for both empirical and theoretical research. The present study investigates the essential intra- and extra-organizational factors in determining the performance of firms using the European Company Survey (ECS) 2019 framework. The evolutionary computation method of genetic algorithm and the machine learning method of Bayesian additive regression trees (BART), are used to model the importance of each of the intra- and extra-organizational factors in identifying the firms' performance as well as employee well-being. The standard metrics are further used to evaluate the accuracy of the proposed method. The mean value of the evaluation metrics for the accuracy of the impact of intra- and extra-organizational factors on firm performance are MAE = 0.225, MSE = 0.065, RMSE = 0.2525, and R2 = 0.9125, and the value of these metrics for the accuracy of the impact of intra- and extra-organizational factors on employee well-being are MAE = 0.18, MSE = 0.0525, RMSE = 0.2275, and R2 = 0.88. The low values of MAE, MSE and RMSE, and the high value of R2, indicate the high level of accuracy of the proposed method. The results revealed that the two variables of work organization and innovation are essential in improving firm performance well-being, and that the variables of collaboration and outsourcing, as well as job complexity and autonomy, have the greatest role in improving firm performance.

Keywords: organizational performance; machine learning; Bayesian additive regression trees; social science; management; deep learning; artificial intelligence; open innovation; firm performance; big data

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1. Introduction

Organizational performance evaluation and quality improvement are essential for labor research and development [1–3]. One of the tasks of a manager is monitoring organizational performance [4,5]. Organizational performance is a broad concept covering what a company produces or the services that it provides [6–8]. In other words, organizational performance refers to how the mission, tasks, and organizational activities of the organization are carried out and in what quality [9,10]. Organizational performance evaluation is one of the issues that the business and academic communities have paid a lot of attention to, and numerous books and articles have been published on the subject [11–13]. Performance evaluation is an effective measure and essential for resource management because not only does it ensure the organization's mission is achieved with optimal performance, but also that the interests of employees and society are met [14–16]. The need for organizational growth and employee excellence urges an effective evaluation system [17–19]. Naturally, the development and implementation of such a performance assessment process would support organizations in achieving their goals by increasing the effectiveness of employees [11,20–22]. The literature suggests two approaches for performance assessment, i.e., subjective criteria approach and objective criteria evaluation approach [23–25]. In the objective approach, the actual figures of the organization are used, but in the subjective approach, the perceived responsiveness is used [26]. Ramstad [27] concludes that a subjective indicator of productivity is essential for measuring productivity for a comparative analysis of different organizations and for producing results with better applicability. There is evidence in the literature that managerial factors are one of the factors influencing the performance of a firm [28]. Managerial factors identify how managers define the organization's ideals and mission and facilitate access to them, create the values needed for long-term success, and apply them through appropriate activity and behavior. These factors can directly or indirectly affect the performance and the working practice of companies [29]. Human resources are another factor whose impact on the performance of firms has been studied and confirmed [30,31].

It had been well studied that relentless market competition, quality, price and speed are three competitive advantages [32,33]. One of the most important factors for entering global markets and developing an economy is to make employees efficient in the production and service sectors [34]. Therefore, many organizations choose a culture of commanding and monitoring and move towards improving innovation culture [35]. Furthermore, organizational structure has a significant effect on improving the performance of firms [36]. Thus, to improve organizational performance, it is necessary to synchronize it with employee well-being [37,38]. For instance, the Finnish Workplace Development Program (TYKES) (2009–2010) empirically supported the interplay between high-involvement innovation practices (HIIPs) and simultaneous improvement of productivity and the quality of working life (QWL) [27]. Information technology is another factor that has a significant effect on improving the performance of enterprises. Today, the trend of change in organizations is so great that instability can be called the most stable feature of organizations, because, with the growth of the World Wide Web and affiliate communication technology, many companies are small- and medium-sized. Based on the Organization for Economic Co-operation and Development (OECD) definition, information and communication technology (ICT) is a set of manufacturing and service industries used to store, transmit, and display data and information electronically [29]. ICT includes factors such as the extent of ICT spread in the organization [39], the rate of information technology updates [40], revenue from the use of technology, and the ability to trade through information technology with customers and suppliers [41,42].

The current study uses the ECS (2019) [43] conceptual framework for evaluating the firm performance. The model, similarly to [43–45], has two outputs, i.e., firm performance and employee well-being. According to this model, two levels of variables affect these outputs: (1) organizational characteristics and (2) external environment. Organizational characteristics include work organization, skill availability and skill development, and employee voice, as also described in [46,47]. Accordingly, the influential variables of the external environment include digitalization, innovation, and product market strategy. At a lower level, "collaboration and outsourcing" and "Job complexity and autonomy" are the variables that evaluate the work organization. In order to assess skill availability and skill development, the variables of "skills requirements and skills match" and "training and skills development" are used. Finally, "direct employee participation" and "workplace social dialogue" (i.e., indirect participation) are used to measure employee voice. In the context of the COVID-19 pandemic, research on new models of work and employment accelerated [48]. Beside remote working and digital platform work, topics such as "Navigating post-COVID workplace innovation evolution: Exploring flexible working models, investing in reskilling and well-being and evaluating new policy trends" are advertised by the scholars of the European Workplace Innovation Network (EUWIN), reflecting the intensified search for new models of work and management practices [49]. In order to assess the originality of these attempts it is worth remembering the former attempts to search for a universal model to renew working practices. For several decades, the academic community, especially scholars of human resource management (HRM), have been stressing the relationship between working practices—especially workplace innovation generating workplace practices—and company-/firm-level productivity (Dortmund/Brussels Position Paper, 2012). The "benchmark"-labeled workplace practices were labeled as the High-Performance Working Practice (HPWP) or High-Performance Working System (HPWS) [45–47]. This type of working practice was characterized by job/task structure giving autonomy and requiring problem-solving, allowing the autonomy of workers, involving them in decision making (direct participation), etc. Companies adopting workplace innovation-generating HPWP/HPWS practice in the US produced significant performance increase (Appelbaum, 2015). Until the last decade – with the exception of the Nordic countries—there were no attempts to explore the roles of factors influencing not only organizational (firm) performance but employees' well-being too [27]. This paper intends to identify the links between the factors shaping a firm's performance and employees' well-being through evaluating human resource managers' perceptions in the EU. The latest European Establishment Survey (2019), covering the EU-27 countries and the U.K., represents a unique possibility to empirically test these links [43]. In the literature, performance evaluation refers to the way missions, tasks and organizational activities are performed. The complex process of the measurement and evaluation of the performance in the forms of efficiency and effectiveness in achieving the of organizational goals fo structural and long-term development is known as firm performance evaluation [50,51]. The performance evaluation has been seen as a controversial management tool in search for the answers to common system design and management problems [52]. Firm performance evaluation evaluates the work completed in terms of quality, quantity, and method of completion during a certain period of time in comparison with the standards.

Considering the trade-off between a firm's performance and employee well-being, the European Company Survey (ECS) 2019 focused on workplaces, and the research concluded that in order to obtain reliable results, what works for employers must also work for workers. Working practices must result in win–win situations. In other words, socially optimal dissemination of the outcomes makes social and economy transaction easier [52]. The ECS 2019 sheds light on how organizations inspire and engage their employees, and whether these strategies maximize employee potential, including formal and implicit skills. In addition, it provides information on an individual's ability to improve performance in the workplace. Successful approaches in this area turn abstract concepts such as human capital into tangible competitive advantages. In other words, as [27] expresses, a strong link between highly engaged innovation practices and simulation productivity and quality benefits both employers and employees. In this regard, novel data-driven models are essential to provide insight into the relationship between input and output variables. Currently, there is a research gap in applying machine learning methods to deliver a model with higher accuracy and performance. In this study, an ensemble machine learning method is accordingly proposed.

2. Background

The literature identifies several links between the innovation, well-being, productivity, quality and firm performance [27]. The ECS 2019 topics include complex work relationships. For example, despite the fact that the European workforce benefits from a high level of education, companies are often facing difficulty in finding skilled workers. A lack of trust can cause management initiatives to fail [53]. For instance, in a work environment where trust is low, employees may be reluctant to share ideas and tacit knowledge about how to improve work processes [54]. Tackling these challenges requires understanding what companies do with the talent and knowledge their employees possess, how they manage employee hiring, and how they attract people inside and outside of the organization's decisions [55]. Of course, how companies use and develop their employees' talents, as well as how they harness and respond to employee voices, must be understood in the broader context of organizational culture, job choice, organizational culture, technology and competitive performance in the product market. In this approach, management pursues knowledge efficiency rather than cost efficiency [56]. The foundation of the current European survey is based on the theoretical framework of strategic human resource management. It develops the concept of innovation in the workplace by linking investment in human resources, participatory work organization, and employee engagement directly and indirectly with measures of performance and company welfare. Under the appropriate conditions, firms profit from investing in human resource systems that promote employee well-being [57]. Indeed, investing in employee well-being helps to ensure the employment relationship is managed well. The employment connection between a company and its workers includes reciprocal beliefs, perceptions, expectations, and informal duties. It incorporates the labor contract, which describes in detail only the most obvious conditions of the exchange of work for money, while mutual duties are defined in very broad terms [58]. Employees and organizations have both complementary and diametrically opposed goals. The labor contract is sufficiently specific to give direction on resolving a limited number of circumstances when interests disagree. Divergent interests must be handled in the remaining circumstances via the continuous link formed by the job relationship, in other words, through a relational contract [59]. Managing divergent interests using relational contracts is contingent upon the parties' ability to exchange [60]. These exchanges may take on a variety of forms and occur at a variety of periods, as workers develop connections with a variety of individuals, for instance, human resources managers, line managers and supervisors, as well as colleagues and team members—and with the company as a whole [54]. The feedback form at the heart of this report is the form in which organizations invest in their employees by implementing workplace practices that improve employee well-being, and employees respond by demonstrating attitudes, motivations, and behaviors conducive to business performance [61]. Proposing advanced data-driven modeling, e.g., [62–65], to bring insight into the work organization, innovation, and performance of an employer for better understanding the involved variables. The application of artificial intelligence and machine learning in modeling the complex relationship of such variables has been limited, however [66–69]. Consequently, in this research, the application of one of the essential machine learning algorithms for modeling organizational performance and well-being is evaluated.

3. Materials and Methods

3.1. Data

The dataset of the ECS 2019 [43] was collected from the period between January to July 2019. It includes information from HR managers and also employee representatives. The survey examines workplace practices, HR management, skills and strategies, and employee involvement, as well as digitalization, innovation and marketing strategies. Figure 1, which is adapted from [43], represents the conceptual framework of the data. In this research, the study is concerned with the following variables, i.e., collaboration and outsourcing, job complexity and autonomy, skill requirements and skill match, training and skill development, direct employee participation, indirect employee participation, innovation, digitalization, product market strategy, employee well-being, and firm performance. Table 1 lists the variables used in our analysis as well as the definitions that this study provides for them.

As with earlier versions, the survey's unit of inquiry was the implementation of local sites. While the majority of enterprises were single-location operations, in case the establishment included several locations, one or more local units were selected in this survey. The target population includes the enterprises with workforces engaging in what are referred to as 'market activities' in the EU countries. In this survey, 98% of investigated establishments were SMEs.

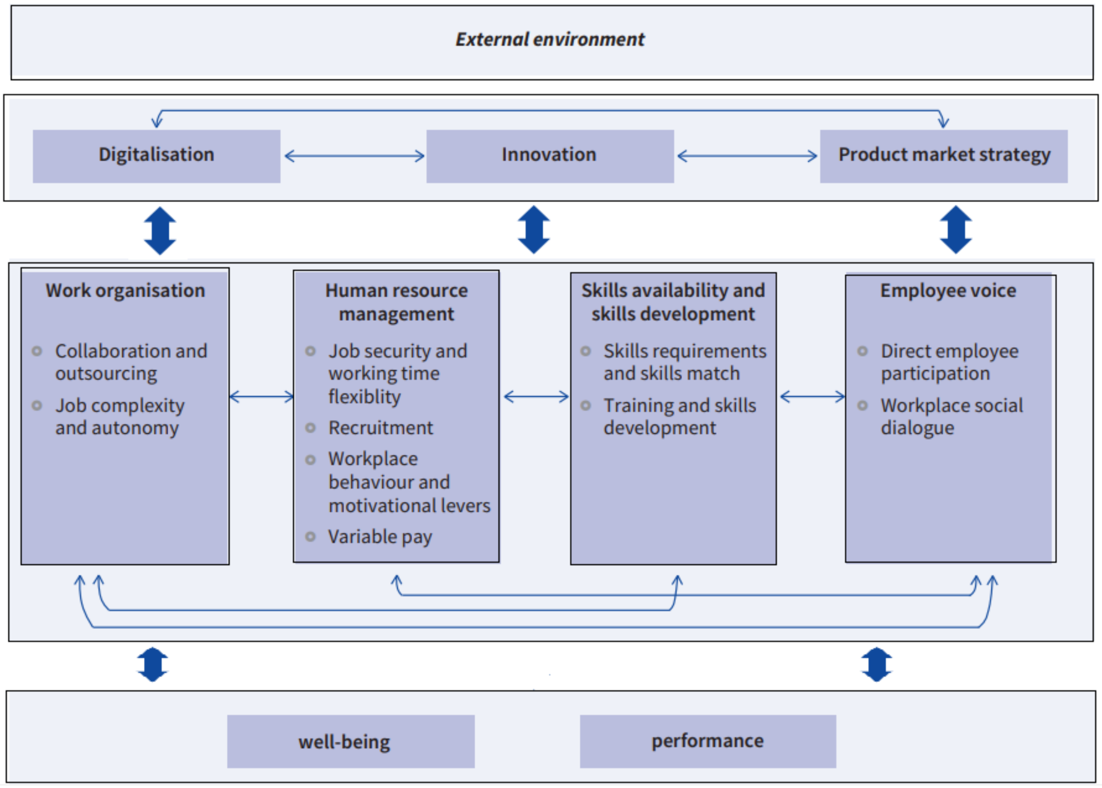

Figure 1. ECS 2019 theoretical framework for firm performance.

Table 1. Variables used in this study and their definitions based on the quantitative analysis.

Main Areas	Factors	Explanation
Work organization	Collaboration and outsourcing	Indicates the extent to which an organization uses outsourcing to carry out its activities.
	Job complexity and autonomy	Indicates the authority of the employees of that organization.
Skill use and skill strategies	Skill requirements and skill match	Explains the extent to which employees' skills match the skills required by the job.
	Training and skill development	Represents the training opportunities of the organization for employee development.
Employee voice	Direct employee participation	Determines the extent to which employees are able to express their needs directly.
	Indirect employee participation	Explains the extent to which employees indirectly express their voice.
External environment	Innovation	Determines the extent to which this organization is a pioneer in innovation.
	Digitalization	Indicates the degree of digitization of tasks and the processes of carrying them out.
	Product market strategy	Specifies what strategies the organization uses.
Outputs	Employee well-being	Indicates the level of employee well-being in the organization.
	Firm performance	Indicates the performance of the organization.

The survey was the first pan-European establishment poll to be conducted through push-to-web technology. This approach was divided into two phases: a telephone screener was used to determine eligibility and select responses for both the manager questionnaire (assigned to the most senior manager responsible for personnel concerns) and the employee representative questionnaire. The questionnaire conductor inquired about the participant contact information. Later, the participant received an online form including the questionnaire. The research included nearly 22,000 managers and around 3000 employee representatives. In certain countries (e.g., Hungary), the sample of employee representative interviews was somewhat small, and hence the findings must be interpreted cautiously. Additionally, their responses may be compared or correlated only with those of management respondents in places where both groups of respondents responded to the questionnaire. The questions used to evaluate each of the variables of the ECS 2019 framework and used in this study is presented in Table S1 in Supplementary Materials.

The European Company Survey (ECS) 2019 is a questionnaire-based representative sample survey in which 21,869 management and 3073 employee representatives for 27 EU Member States (Austria, Italy, Belgium, Latvia, Bulgaria, Lithuania, Croatia, Luxembourg, Cyprus, Malta, Czechia, Netherlands, Denmark, Poland, Estonia, Portugal, Finland, Romania, France, Slovakia, Germany, Slovenia, Greece, Spain, Hungary, Sweden, and Ireland) were interviewed [44]. Because the units of measurement of data (i.e., the answers to different questions) are different, for quantitative analysis, the data must first be unified. For example, in the ESC model, two variables, "collaboration and outsourcing" and "job complexity and autonomy", are used to evaluate "work organization". Eight questions have been designed to measure complexity and autonomy, and the answer to one of the questions is yes or no, while to answer two of the eight questions, the respondent must choose one of the two options. This disparity in the units of measurement of the queries makes the task of quantitative data analysis difficult. Hence, the questions were initially modified and merged, and all questions were redesigned in such a way that the answers can be either zeroes or ones. For example, the questions that were yes or no were given the value of one for the answer yes, and given the value of zero for the answer no. In the questions where the respondent needed to choose an option, the option that was not selected was given the value of zero, while the selected option was given the value of one. After integrating the units and the questionnaire questions, the data entered the next stage for quantitative analysis. First, the factors were tested, and the features were selected. Feature selection (FS) [70], which is a dimensionality reduction strategy, eases the learning process from data sets [71]. To select the feature, a genetic algorithm (GA) [72] was used to identify the factors (i.e., questions of the questionnaires) that played a role in determining the performance. GA is a metaheuristic method that aims to find the maximum number of factors affecting the dependent variable. It should be noted that the FSinR package in R software was used to run the GA [73]. After identifying the influencing factors, or in other words, after confirming the effect of the model variables on the firm performance, the Bayesian additive regression trees (BART) model was used to determine the importance of each factor in shaping the performance of the firms and employee well-being.

3.2. Methods

3.2.1. Genetic Algorithms

The genetic algorithm model selects the best independent variables that have the largest share in determining changes to the dependent variable [74]. In other words, the GA helps to optimize the model input variables to effectively define the output variable [75]. The GA is performed in twenty rounds, each round is named as a population, and the output of the population that had a higher fitness is considered as the input variable of the model [76,77]. Table S2 in the Supplementary Materials shows the output of GA for the performance variable. To measure firm performance, four questions were designed in the ECS 2019 model, and these four questions were coded to prodvol_68, profit_69, profplan_70, and chempfut_71 in this study, which are displayed in columns in Table S2. The first column of Table S2 is related to the model input variables, or the ECS 2019 model questionnaire questions. The first line of this table, labeled as population, refers to the population (or round) in which the genetic algorithm had the highest fitness, and for summary, only the populations with the highest fitness are listed in this table. The results related to the rest of the populations are attached to this report as an Excel file. The interpretation of Table S2 in the Supplementary Materials is that if a variable is selected as the input variable, it is given the value of 1, otherwise it takes the value of 0. This means that only the input variables that take the value of 1 for question 68 were used in the next step and the rest of the variables were ignored. It should be noted that one input variable may be selected for one output variable but not for other output variables. Finally, the last row of Table S2 shows the fitness of the GA model for each output variable, which indicates the accuracy of this step of the GA in selecting the input variables for the respective output variable. This fitness makes sense compared to the outputs of the other populations, and as mentioned, only the output that had the highest fitness is listed in this table. All the mentioned steps were performed for the dependent variable of employee well-being, the output of the GA model for this variable is presented in Table S3, and the questions designed by the ECS 2019 model for evaluating the employee well-being were given the codes sickleave_59, lowmot_60, retainemp_62, and qwprel_63 in Table S3 in the Supplementary Materials.

3.2.2. Bayesian Additive Regression Trees (BART)

BART is an efficient ensemble method for machine learning [78]. Within the past decade its popularity has been increasing and it has been applied in a diverse range of applications, e.g., [79,80]. It functions based on several decision trees in which parameters of the model are regularized in advance [78]. BART is known as a nonparametric Bayesian method with regression which uses dimensionally adaptive random basis elements. BART is part of the family of boosting algorithms used for statistical modeling based on priors and likelihoods. In this learning method, several decision trees are involved simultaneously, as described by Equation (1):

$$y_i = \sum_{l=1}^{m} g(x_i;\ T_l,\ M_l) + \varepsilon_i \tag{1}$$

where $\varepsilon_i \sim N\left(0, \sigma^2\right)$, and $E(Y \mid x_i)$ is the integral of μ_{bl} for the essential nodes directed to x_i by $g(x_i;\ T_l,\ M_l)$. The predictive performance of BART is very high among smaller numbers of trees (i.e., m in the Equation (1)). In the BART learning approach, $p(T_l)$ states the structure of the proposed decision tree, and $p(\mu_{bl} \mid T_l)$ defines the parameter values in the essential nodes. In addition, $p(\sigma)$ defines the independent variances. Considering the tree l's depth d and probability calculations, it is worth defining that the prior $p(T_l)$ determines the depth of the tree as $d \in [1, \infty)$ and further assigns the probabilities of each note via $\alpha(1+d)^{-\beta}$ with a $\alpha \in (1, 0)$ and $\beta \in [0, \infty)$. For increasing the probabilities of smaller trees, the approach initializes default values, i.e., $\alpha = 0.95$ and $\beta = 2$ as. To calculate the prior $p(\mu_{bl} | T_l)$ for the terminal node values, Equation (2) is used:

$$\mu_{bl} \sim N\left(0, \sigma_\mu^2\right) \tag{2}$$

where $\sigma_\mu = e / \left(k \sqrt{m}\right)$, which lowers probabilities to higher values and aims at decreasing the μ_{bl} value toward zero. An inverse X^2 distribution is the prior for the variance σ^2. In addition, the partial residuals in this backfitting algorithm are calculated by Equation (3):

$$R_l \equiv y - \sum_{k \neq 1} g(x; T_k, M_k) \tag{3}$$

where the conditional values of T_l, M_l, and the residual SD ($\sigma \mid T_1, \ldots, T_m, M_1, \ldots, M_m$) are supported through using an inverse distribution of gamma. The equation further provides $(T_1, M_1) \ldots (T_m, M_m)$ sequences which converge to the posterior distribution as follows:

$$P(\sum_{l=1}^{m} g(.; T_l, M_l)|Y) \tag{4}$$

For predictive functionality, consequently, BART uses a subset of variables for expansion and splitting the trees. In doing so, many backward stepwise selection procedures are recommended to quantify the reduction in mean square error [81] to rank predictors by importance. Besides, $p_{vi} = 1/Q$ for all $x \in \{1, \ldots, Q\}$ describes the proportion for each variable inclusion. According to the BART method, variables are ranked from zero to one hundred based on their importance in determining changes to the output variable. The variable that has the greatest impact on explaining changes in the output variable is given a value of 100 and the variable that has the least impact on the output variable compared to other variables is given a value of zero. Tables S4 and S5 in Supplementary Materials, show the BART model output for the questions prodvol_68, profit_69, profplan_70, and chempfut_71, which represent the performance variable, and questions sickleave_59, lowmot_60, retainemp_62, and qwprel_63, which represent employee well-being. Table S4 in the annex shows that there are different input variables for each query related to the firm performance variable, and these variables have different importance in determining the output variable.

4. Results and Discussions

4.1. Firm Performance and Employee Well-Being

The ECS 2019 framework includes two outputs called firm performance and employee well-being. In other words, this framework has two dependent variables and the interaction among other variables determines the changes in these two variables. Therefore, the ECS 2019 framework was divided into two models, one that measures performance and the other that measures employee well-being. After that, both the selection of features and the determination of the importance of features were carried out twice and each time for an output variable. The input variables selected from the GA stage based on the ECS 2019 framework are presented in Tables 2 and 3. Table 2 shows the importance of establishment characteristics in influencing firm performance. For this purpose, the importance of input variables was averaged. For example, the importance of the questions designed to measure "collaboration and outsourcing" was averaged and considered as a variable. Comparison of the average importance of the variables shows that the variables "collaboration and outsourcing" and "job complexity and autonomy", which are sub-variables of "Work Organization", with an average of 91 and 37.7 have, respectively, the most importance in the performance of firms compared with other establishment characteristics. This finding shows how the implementation of task structure in the organization is important, and how much outsourcing and collaboration can affect the performance of firms. On the other hand, this finding reveals that the more authority the employees have in the organization, the higher their performance. It was also found that the development of staff skills is more important than the staff's skills match with tasks. Although matching the skills required for a task with the skills of the individual is important, the findings of this study disclose that training, developing and updating the skills of employees is of greater importance. In general, after work organization, "skills availability and development" is another organizational characteristic that is most important in influencing firm performance. Another organizational characteristic that was examined in this study is the voice of employees. This feature has two sub-variables: workplace social dialogue (or indirect participation) and direct employee participation. The findings also indicate that, despite the fact that workplace social dialogue has the least impact on firm performance compared to other organizational characteristics, direct participation of employees with an importance of thirty-one is an important organizational feature in determining firm performance. In general, it was found that among the organizational characteristics, the employee voice has the least contribution of changes in firm performance.

Table 2. BART model for the importance of establishment characteristics in the firm performance.

		Establishment Characteristics					
		Work Organization		Skill Availability and Development		Employee Voice	
		Collaboration and Outsourcing	Job Complexity and Autonomy	Skill Requirements and Skill Match	Training and Skill Development	Workplace Social Dialogue (i.e., Indirect Employee Participation)	Direct Employee Participation
Performance	68	90.86553	36.77524	15.70021	36.62362	15.42219	29.8731
	69	91.33749	38.66197	29.07501	37.71609	16.86107	29.69314
	70	88.87332	41.083	33.32589	36.5229	13.84198	31.26136
	71	93.29859	34.45313	27.06142	28.60742	23.52169	33.35558
Average		91.0937325	37.743335	26.2906325	34.8675075	17.4117325	31.045795

Table 3. BART model for the importance of external environment factors in a firm's performance.

		External Environment		
		Innovation	Digitalization	Product Market Strategy
Performance	68	87.71154	39.42021	42.98512
	69	65.5324	31.15723	39.56193
	70	56.75349	31.70829	40.3744
	71	73.39461	36.36043	47.30762
Average		70.84801	34.66154	42.5572675

Table 3 summarizes the importance of external environment factors in influencing the performance of the firm. The last row of Table 3 shows how, on average, each of the external environment factors, namely innovation, digitalization, and product market strategy, are important in determining changes in firm performance. The output of the BART machine learning model shows that innovation has the greatest impact on firm performance. Although innovative organizations and those who are the first to follow innovation are always at higher risk, the findings of this study show that following innovation, after collaboration and outsourcing, has the greatest role in improving the performance of a firm. After innovation, market product strategy, with a magnitude of 42.5, is the second most important external environment factor affecting the performance of a firm and, in general, the third most important factor affecting firm performance. Digitization is another external environment factor that has a great influence on completing tasks in the organization and, both directly and indirectly, by influencing other organizational factors, has a significant role in determining firm performance. Digitization requires new infrastructure and new skills and also affects the way tasks are performed in organizations. In general, among all the nine variables examined in this study, digitalization was ranked sixth in terms of the impact on firm performance, after collaboration and outsourcing, innovation, product market strategy, job complexity and autonomy, and training and skill development.

Table 4 demonstrates the output accuracy of the BART model using different accuracy metrics. R2 shows that 89% of the changes in the output variable 68 are expressed by the input variables of the model. By the same token, the input variables of questions 69, 70 and 71 explain 93%, 92% and 91% of the changes, respectively, which is significant. In fact, the accuracy metrics presented in Tables 4 and 5 show how reliable the findings presented in Tables 6 and 7 are. Due to the low level of errors (i.e., mean absolute error (MAE), mean squared error (MSE), and root mean square error (RMSE)) and the high rate of R2, the performance of the BART learning machine model can be evaluated as significant in determining the importance of intra-organizational and extra-organizational variables in a firm's performance.

Table 4. Accuracy metrics of the BART model.

	prodvol_68	profit_69	profplan_70	chempfut_71	Mean
MAE	0.27	0.22	0.17	0.24	0.225
MSE	0.08	0.06	0.05	0.07	0.065
RMSE	0.28	0.25	0.22	0.26	0.2525
R2	0.89	0.93	0.92	0.91	0.9125

Table 5. The output of the BART model for the importance of establishment characteristics in employee well-being.

		Establishment Characteristics					
		Work Organization		Skill Availability and Development		Employee Voice	
		Collaboration and Outsourcing		Job Complexity and Autonomy	Skill Requirements and Skill Match	Training and Skill Development	Workplace Social Dialogue (i.e., Indirect Participation)	Direct Employee Participation
employee well-being	59	92.1	41.72	26.16	32.46	13.91	30.02
	60	-	37.5008	28.85518	33.953	14.9376	33.06341
	62	90.09591	35.41285	28.28817	29.71831	14.58434	29.07575
	63	100	51.51211	33.81739	47.88896	20.10311	39.84083
Average		94.06530333	41.53644	29.280185	36.0050675	15.8837625	32.9999975

Table 6. The output of the BART model for the importance of external environment factors in employee well-being.

		External Environment		
		Innovation	Digitalization	Product Market Strategy
Employee well-being	59	70.15	41.33	40.54
	60	60.90469	34.08269	39.25492
	62	63.39849	34.68857	41.36512
	63	75.955	40.61766	49.95633
Average		67.602045	37.67973	42.7790925

Table 7. Accuracy metrics for running the second model.

	sickleave_59	lowmot_60	retainemp_62	qwprel_63	Mean
MAE	0.19	0.16	0.22	0.15	0.18
MSE	0.06	0.04	0.06	0.05	0.0525
RMSE	0.24	0.21	0.25	0.21	0.2275
R2	0.88	0.87	0.92	0.85	0.88

Figure 2 illustrates a graphical representation of the importance of each of the intra-organizational and extra-organizational variables in determining employee well-being. On average, external environment factors have a greater impact on employee well-being than organizational characteristics.

Figure 2. The importance of intra-organizational and extra-organizational factors in firm performance.

4.2. Factors Shaping Employee Well-Being

The test results of the second model of this study, which identifies the factors affecting employee well-being, are summarized in Tables 5 and 6. The last row of Table 5 shows that, similarly to the previous model, i.e., the importance of establishment characteristics on the performance of the firm, the impact of "collaboration and outsourcing" and "job complexity and autonomy", which are sub-variables of the work organization, with an importance of 94 and 41.5 out of 100, have the greatest impact on employee well-being. After that, "skills availability and development", with two sub-variables, "skills requirements and skills match" and "training and skill development", with an importance of 28.8 and 33.9, respectively, have the greatest impact on determining employee well-being. Finally, the employee voice variable, which consists of the variables of workplace social dialogue (i.e., indirect participation) and direct employee participation, is of the utmost importance in determining employee well-being. It should be noted that, although the employee voice variable has the least impact on the dependent variable on average, the importance of direct employee participation is very important to employee well-being. However, "workplace social dialogue", with an average of 15, is the least important variable in explaining changes in employee well-being.

Table 6 summarizes the importance of external environment factors in influencing employee well-being. The last row of Table 6 shows how, on average, each of the external environment factors, namely innovation, digitalization, and product market strategy, are important in determining changes in employee well-being. The output of the BART machine learning model shows that innovation has the greatest impact on employee well-being. The findings of this study show that innovation, after collaboration and outsourcing, has the greatest role in improving employee well-being. After innovation, market product strategy, with a magnitude of 42.7, is the second most important external environment factor affecting employee well-being, and in general the third most important factor affecting employee well-being. Digitization is another external environment factor that has a great importance on employee well-being. In general, among all the nine variables examined in this study, digitalization was ranked fifth in terms of the impact on employee well-being, after collaboration and outsourcing, innovation, product market strategy, and job complexity and autonomy.

The study of accuracy metrics of the second model shows that the accuracy of this model is also very high, and the summary of these metrics is given in Table 7. Due to the low level of errors (i.e., MAE, MSE, and RMSE) and the high rate of R2, the performance of the BART learning machine model can be evaluated as significant in determining the importance of intra-organizational and extra-organizational variables in employee well-being.

Figure 3 illustrates a graphical representation of the importance of each of the intra-organizational and extra-organizational variables in determining employee well-being. On average, external environment factors have a greater impact on employee well-being than organizational characteristics.

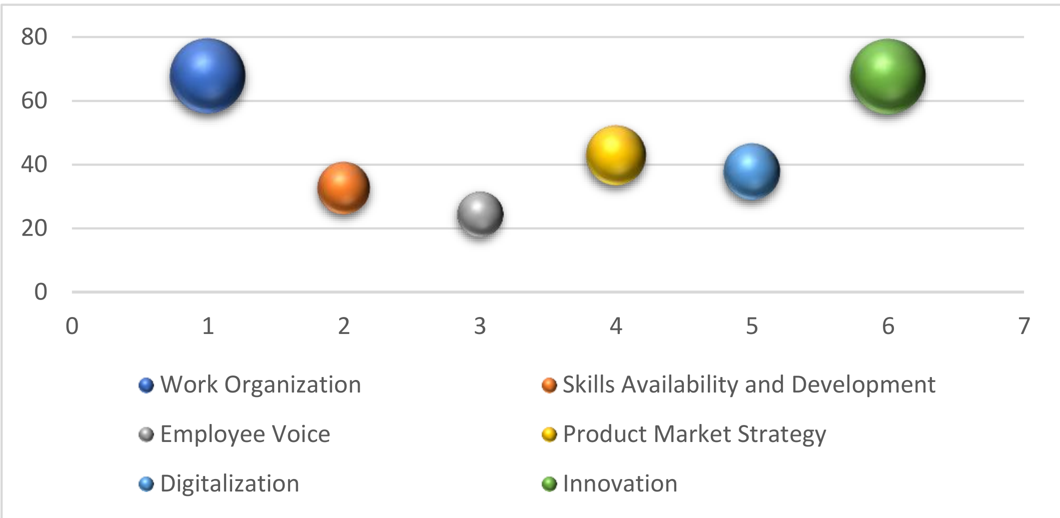

Figure 3. The importance of intra-organizational and extra-organizational factors in employee well-being.

Considering the firms' performance and the dominant role of work organization and innovation, the findings disclosed that the variables of collaboration and outsourcing, and innovation, were the most important both in determining the performance of firms and in improving the well-being of employees. On the other hand, it was found that workplace social dialogue (i.e., indirect participation) had the least impact on both performance and employee well-being. Examination of the studied variables at a higher level reveals that among the establishment characteristics factors, the work organization had the greatest impact on firm performance, and among the external environment variables, innovation had the greatest impact on firm performance. After the work organization variable, the skill availability and development variable and the employee voice variable were other establishment characteristics that played a role in determining firm performance. Innovation, product market strategy and digitalization were the external environment variables that were important in determining the performance of firms (see Figure 4). Although on average the employee voice was the least important in determining firm performance, a careful study of the variables of organizational characteristics shows that direct employee participation is among the most important and influential factors of organizational characteristics that affects performance. However, workplace social dialogue (i.e., indirect participation), or in other words, indirect employee participation, had the least impact on performance compared to the other variables studied, which led to a decrease in the average impact of employee voice on performance.

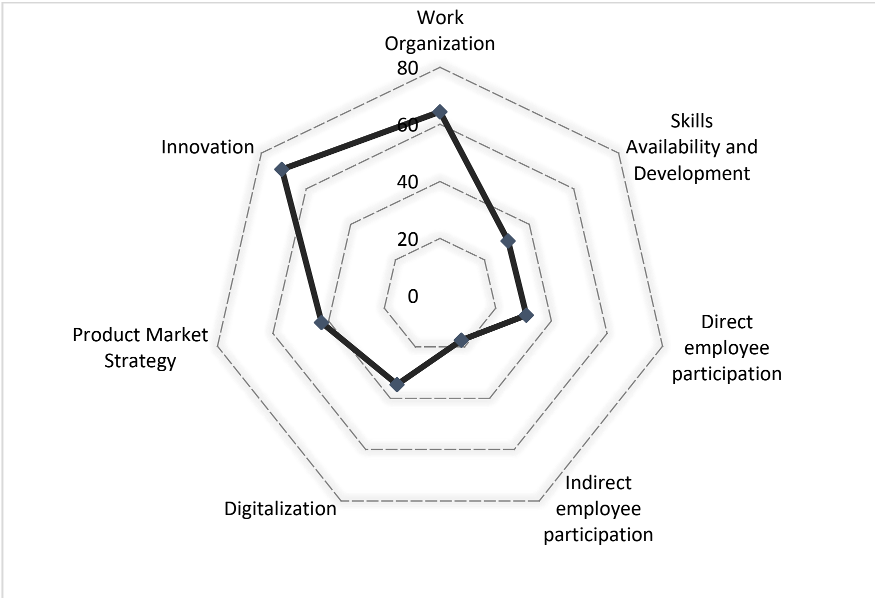

Figure 4. The importance of intra- and extra-organizational factors in performance.

Considering the factors affecting employee well-being, and the dominant role of work organization and innovation, the study of important and influential variables on employee well-being reveals that, like the variables affecting firm performance, work organization, skill availability, development, and employee voice are the establishment characteristics which most affect employee well-being. In addition, the variables of innovation, product market strategy and digitalization are the external environment factors that are most important in determining employee well-being (see Figure 5). The important point here is the importance of the employee voice in determining employee well-being. As shown in Figure 5, the employee voice was the least important variable in terms of employee well-being, while the importance of the two variables workplace social dialogue (i.e., indirect participation) and direct employee participation was averaged, and the result was considered significant in terms of the employee voice. In fact, looking at Table 8, direct employee participation is one of the influential factors in shaping employee well-being.

Figures 4 and 5 are devoted to representing the importance of intra- and extra-organizational factors on performance and employee well-being, respectively. The output of the BART model indicates that, among the intra-organizational factors, outsourcing has the greatest impact on shaping both the performance of companies and creating a platform for improving the well-being of employees. This finding emphasizes the importance of organizational structure and collaboration with other entities in the value chain. In other words, these findings state that the impact of an employee's skills on improving the performance of the organization is less than the impact of collaboration with business partners. Companies that outsource more activities have reported higher employee well-being as well. This implies that, in organizations whose structure is more flexible to working with other partners, their employees report higher levels of satisfaction and motivation. Among the external environmental factors, it was found that innovation is the factor that has had the greatest impact on both organizational performance and employee well-being. This finding indicates that innovative organizations and those who have designed mechanisms to exploit innovation have both reported higher organizational performance, and their employees have shown greater satisfaction and motivation to work in these environments (see Table 8). For future research, applying the proposed method for modeling the other similar variables, e.g., [82–84] is suggested. Research on the effects of open innovation on firms' performance has recently become a popular topic [85]. Several studies, e.g., [86–88], emphasized the interconnection and influence of the close relationship between open innovation and firm performance. To further investigate this interesting realm, using similar machine learning methods are recommended for better modeling the effects of open innovation on firms' performance.

Figure 5. The importance of intra- and extra-organizational factors in employee well-being.

Table 8. Performance evaluation and employee dimensions and the contents with the average importance.

Level	Area	Focus	Firm Performance	Employee Well-Being
Establishment Characteristics	Work Organization	Collaboration and outsourcing	91.0937325	94.06530333
		Job complexity and autonomy	37.743335	41.53644
	Skill Availability and Development	Skill requirements and skill match	26.2906325	29.280185
		Training and skill development	34.8675075	36.0050675
	Employee Voice	Workplace social dialogue (i.e., indirect participation)	17.4117325	15.8837625
		Direct employee participation	31.045795	32.9999975
External Environment	Innovation		70.84801	67.602045
	Digitalization		34.66154	37.67973
	Product Market Strategy		42.5572675	42.7790925

Considering future research, it is also worth discussing the limitations of the study. One of the limitations of the study is that the perspective of the employees' representatives was not included. In fact, the study was carried out based on the views of the human resource managers in European organizations. This is important because variables such as employee well-being, employee voice, and skill match were all evaluated using a managerial perspective. Hence, there is room for another study that examines this issue with a more comprehensive perspective, in which in addition to the perspective of the managers, the perspective of employees or their representatives is also examined simultaneously. On the other hand, to test the conceptual model, data related to all European organizations studied in the ECS 2019 survey were integrated, and the purpose of the study was only to theoretically examine the factors affecting firm performance and employee well-being, while the impact of the institutional environment in which the organization embedded have been ignored. It is therefore proposed for future research to examine how institutional differences (i.e., labor market regulation, collective organizations of employees and employers, education and training system) prevailing in different European countries affect the performance of establishments and employee well-being.

5. Conclusions

Achieving the goals of an organization depends on the ability of human resources to perform the assigned goals. Human resource is often regarded as a critical aspect in achieving organizational objectives and enhancing their efficiency. Thus, enhancing both performance and employees' well-being at the same time is an unavoidable need for sustainable businesses' success too. Consequently, the present study identifies the factors affecting the formation of firm performance and employee well-being and ranks them based on their importance. For this purpose, the theoretical framework and the dataset of the ECS 2019 were used to propose a novel model based on machine learning. Findings from the genetic algorithm and BART machine learning model disclosed that work organization and innovation are the most important variables in enhancing both firm performance and increasing employee well-being. In other words, this study shows that the influence of an employee's talents in boosting the performance of the firm is smaller than the impact of cooperation with business partners. Companies that outsource more tasks have reported improved employee well-being as well. This means that in the firms whose structure is more adaptable to working with other partners, their employees report better levels of satisfaction and motivation.

Furthermore, among the external environmental elements, it was revealed that innovation is the one that has had the largest influence on both organizational success and employee well-being. This research demonstrates that the firms who have established methods to exploit innovation have both reported superior organizational performance and their employees have exhibited more willingness to work in such contexts. Thus, it is suggested that organizations, in order to increase their performance, on the one hand, pay more attention to collaboration and outsourcing, as well as job complexity and autonomy, and on the other hand, provide an environment for producing and implementing innovation in organizations.

Supplementary Materials: The following are available online at https://www.mdpi.com/article/10.3390/joitmc8040177/s1, Table S1: Questions evaluating the variables used in this study, Table S2: The output of Genetic Algorithm for the first model, Table S3: The output of Genetic Algorithm for the second model, Table S4: The output of BART analysis for the first model, Table S5: The output of BART analysis for the second model.

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Abbreviations

BART	Bayesian Additive Regression Trees
CART	Classification and Regression Tree
ECS	European Company Survey
EFQM	European Foundation for Quality Management
FS	Feature Selection
GA	genetic algorithm
HIIPs	high-involvement innovation practices
ICT	Information and Communication Technology
MAE	Mean Absolute Error
MCMC	Markov Chain Monte Carlo
MSE	Mean Squared Error
OECD	Organisation for Economic Co-operation and Development
PMS	Performance measurement system
RMSE	Root Mean Square Error
SMART	Strategic Measurement and Reporting Technique

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