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Innovation in Company Labor Productivity Management: Data Science Methods Application

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Abstract: The article considers the challenge of labor productivity growth in a company using objective data about economic, demographic and social factors and subjective information about an employees' health quality. We propose the technology for labor productivity management based on the phased data processing and modeling of quantitative and qualitative data relations, which intended to provide decision making when planning trajectories for labor productivity growth. The technology is supposed to use statistical analysis and machine learning, to support management decision on planning health-saving strategies directed to increase labor productivity. It is proved that to solve the problem of employees' clustering and design their homogeneous groups, it is properly to use the *k*-means method, which is more relevant and reliable compared to the clustering method based on Kohonen neural networks. We also test different methods for employees' classification and predicting of a new employee labor productivity profile and demonstrate that over problem with a lot of qualitative variables, such as gender, education, health self-estimation the support vector machines method has higher accuracy.

Keywords: data science; statistical data processing; predictive analytics; machine learning; classification; clustering; labor productivity; health management; health-saving strategies; electric power industry

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1. Introduction

Rapid modernization and technological innovations inevitably actualize the problem of human capital development. The human capital quality including health quality significant contributes to the labor productivity growth. The main idea of the study is to argue the importance of investment in maintaining the personnel health in order to provide the labor productivity growth of a company, as well as to design a new technology and models for such decisions implementation.

Labor productivity growth and priority economies' sectors modernization are necessary conditions for economic development and important elements of national security. Labor productivity is a key indicator of a countries' economic development and determinant of standard of living. Russian national project "Labor productivity increasing and employment support" [1], supposes target indicator as increasing labor productivity in companies. At the same time, decisions such problems as labor productivity improvement, companies' performance and competitiveness growth, industries and regions development depend on the preservation of human health and its safety.

As an economic characteristic for labor and production efficiency labor productivity shows value of labor costs required to produce a product unit. Traditionally factors, facilitated to labor productivity improvement [2–5], are combined into the following groups:

- Material and technical factors, in that number technology innovations;
- High-performance workspace setting up;

- Development, specialization and concentration of production, using lean production techniques;
- Improvement of production structure and output volumes;
- Advanced training;
- Social and economic factors determined wages and working conditions.

As is shown from the above human potential factor such as employee health quality is not considered as productive and target [6–8]. For a thorough analysis of the substantive foundations of this problem, there are no appropriate methods for quantitative assessment the impact the personnel health on labor productivity, which is to be a basis for decision support and strategies creation in health management in order to increase labor productivity and to provide the growth of operational efficiency of a company.

We determine the human health in accordance with recommendations of the World Health Organization (WHO) [9] as "a state of complete physical, mental and social well-being, and not just the absence of diseases and physical defects." Health state, social skills and knowledge reflect human potential. The growth of the human potential quality directly affects the performance indicators of companies, organizations, institutions and economies in general.

The state and quality of human health as a factor of workforce productivity has not been sufficiently studied in scientific works. Probably, this problem will come to the fore after other mechanisms and sources of labor efficiency growth have been exhausted: production modernization and digitalization, organization improvement and others. Under fourth industrial revolution, the workforce quality moves from insignificant to the most important factors in a labor productivity management.

The issues of personnel health protection in companies' human resource management are presented in [10–12], in which the existing labor protection quality management system is analyzed and mechanisms for its improvement are proposed. Health factors are also taken into account when building quality management systems [13]. Health as a part of human capital, and health preservation as an element of the corporate social responsibility system is considered in [14–17]. Assessment of health care system effectiveness at the macroeconomic level, analysis of the effectiveness of health preservation investments and their impact on economic growth are given in [18–29].

A qualitative analysis based on expert assessments of the impact of the personnel health level on labor productivity is carried out in [30,31], also is regularly presented in the WHO reports and OECD reports [8,9,32]. Many research are devoted to the approaches design for the labor productivity growth as a company competitiveness factor, supposed methods for searching, training and promoting talent [33–36]. A set of leading indicators characterizing the labor conditions and value-motivational environment are presented in [37–39]. The economic returns to health and the impact of health on employment and wages are discussed in the works [40,41]. An assessment of the influence of the employee's age on a labor demand, taking into account the decrease in health potential with the age of a person, is given in the works [42].

In a number of publications, the enterprises is considered with the notion of organizations as complex social systems. Complex interdependent relationship between organizational effectiveness, employees' health and quality culture are explored in [43]. According to the systematic view of work organizations, employee health is closely tied to organizational effectiveness. Building a healthy organizational culture is critical to promoting organizational effectiveness and employee health [44–46]. Considering the interests of employers to improve the employee's health quality in order to company efficiency growth, several studies are examining the impact of measures n future labor market outcomes of employees [47].

Indeed, it is profitable for businesses to invest in employee health for several reasons. First, workers with health problems have a higher probability of receiving payments from the employer for sick leave. This is important not only for the enterprise, but also for the public administration system, since it is of interest for policy makers whether such employer policies reduce dependency rates and if so, whether the effects are sufficiently large to justify their active promotion using public funding. Secondly, reduced turnover due to improved worker-firm matches not only reduces turnover costs for firms. Finally, health-improving measures adopted by firms may increase the labor market attachment of elderly workers, thus alleviating the negative effects of the demographic change in terms of both shortages of skilled workers. In addition to these obvious financial benefits for enterprises to improve the quality of employee health, it should be noted that a comprehensive approach to assessing the quality of employee health and its impact on a labor productivity growth has not been presented to date, and based on the information received, the development of differentiated measures to improve the quality of employee health has not been presented for their homogeneous groups. After all, the grouping of employees into qualitatively homogeneous groups makes it possible to reduce the costs of health-preserving measures, speed up the process of organizing such measures and ensure the fastest growth in labor productivity and efficiency of the enterprise as a whole.

Analysis of existing approaches, methods and models of personnel health and labor productivity management, a number of significant shortcomings of the presented approaches have been identified, limiting the scope of their application: there are no methods for quantitatively assessing the impact of the level and state of health on labor productivity and further recommendations for forming a complex of management decisions, aimed at increasing a labor resources efficiency, taking into account the quality of these resources. The problem associated with the study of heterogeneous factors of labor productivity, including factors of personnel health, with engineering the models to reveal type and nature of the relationships between these factors, with determination homogeneous employees having similar labor productivity profiles in order to manage it, is quite relevant and meaningful over digital transformation of an economy. This necessitates the development of a new approach, technology and supporting models that reflect the essential properties of the socio-economic system of enterprises—the high dynamics of ongoing processes, the uncertainty of the internal and external environment.

In this work, we put forward a hypothesis that for a more complete and comprehensive description of labor productivity as a management object, in addition to economic factors, it is necessary to take into account social, demographic and factors characterizing the personnel health. The study is aimed at justifying the feasibility of financial investment in maintaining a personnel health in order to ensure the labor productivity growth of enterprises as well as design of the technology and models of such investment.

The objective of this study is to develop a technology for labor productivity management of a company, taking into account heterogeneous information about economic, demographic, social factors, as well as information about the quality factors of personnel health, and providing decision-making support in planning labor productivity growth trajectories. To achieve the formulated goal, we solve following problems:

- Identification and substantiation of a set of factors, including factors about health quality that determine labor productivity;
- Design homogeneous employees' groups using all indicated above factors;
- Development a set of management decisions to improve personnel health quality which is differ for each homogeneous group and to contribute to labor productivity growth;
- Assessment of economic efficiency of supposed management decisions to preserve personnel health.

We also note that issues related to occupational health and safety, reduction of occupational injury risks are not considered in this study. Factors reflected employees' health potential and provided their opportunity to perform professional duties, as well as the employers' desire to influence this potential to maintain, to increase and to contribute to the labor productivity growth are considered in this research.

The methodology of the research includes human capital theories, methods of system analysis and modeling of social and economic processes, methods statistical modeling, methods of cluster analysis, methods of decisions making under complexity. The research materials are statistical data and operational reports about large company of the electric power industry, as well as data about employees' survey conducted in this company.

2. Methodology of Research

2.1. Conceptual Approach for Labor Productivity Management

We propose the technology based on step-by-step data processing and modeling. It reflects demographic, social factors and factors about the personnel health quality. The conceptual diagram of this approach is shown in Figure 1 and is aimed to labor productivity management. The technology is implemented by stages.

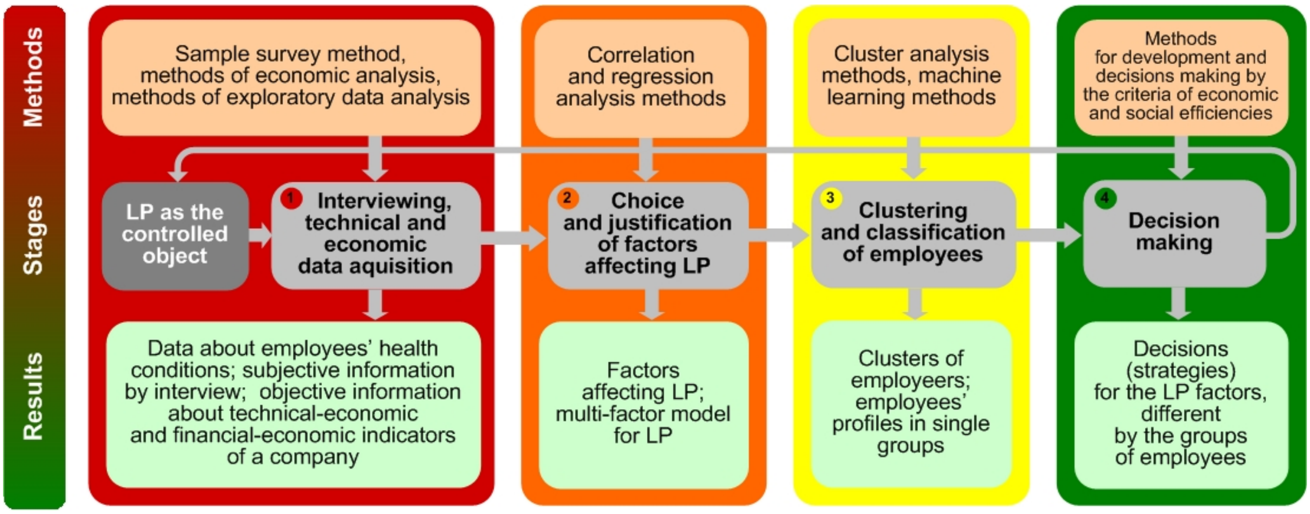


Figure 1. Conceptual scheme of technology for labor productivity (LP) management.

Stage 1. Qualitative analysis of the personnel health status, technical and economic data acquisition. A continuous examination of the company's employees is carried out using medical examinations and questionnaires. The result of this stage is objective data about health state of employees as well as subjective information about the health state and its quality.

Stage 2. Selection and substantiation of factors affecting the personnel individual productivity. An exploratory data analysis is carried out, an assessment of the influence of factors reflecting the social and demographic personnel characteristics as well as factors determining the influence of the health state and its quality on the labor productivity is conducted on the basis of correlation and regression analysis methods.

Stage 3. Employers' clustering (grouping) into homogeneous groups and composition typical personnel profiles for each cluster. The personnel with similar demographic, social factors and health quality are united into homogeneous groups. The result of this stage is the personnel typical profiles by the clusters.

Stage 4. Development of management decisions aimed at improving the state and quality of personnel health for each homogeneous employers' cluster.

2.2. Materials and Methods

The hypothesis and the developed technology are verified on empirical data from a large electric power company in Russia. The experiment was conducted in 2020, in which more than 700 employers from the technical, planning and financial departments took part. To collect data, a survey of all employees was carried out in accordance with the questions, see Appendix A (Table A1). A qualitative analysis of the health status of an employee is carried out using a developed questionnaire consisting of 30 questions, reflecting the self-assessment of the personnel of their health. The processing of the results is carried out on the basis five indicators characterizing different health conditions of the personnel, see Appendix A (Table A2). The assessment procedure of the survey results is assessed by four experts.

In addition to objective data on employees was collected using the company's data bases about employees' education, marital status and number of children. The calculation of labor productivity was implemented in accordance with the algorithm described in Section 3.1. Data analysis and modeling is made in Statistica 10.0 software.

Statistical machine learning methods as a part of data science methods differ from classical statistical methods in that they data driven and do not seek to describe that data with a linear or other general function. Machine learning tends to put a lot of emphasis on developing efficient algorithms that scale to large amounts of data in order to optimize a predictive model. Below is a brief description of the machine learning methods used in the work.

2.2.1. Decision Trees

Decision tree models are a classification model and powerful predictive modeling tool in data science. The decision tree model is based on recursive partitioning—multiple division of data into sections and subsections in order to create homogeneous classes in each summary subsection. A tree model is a set of "if-then-else" implication rules. Trees have the ability to discover hidden patterns corresponding to complex data interactions. A model can be expressed in terms of relationships between predictors that is well interprete. The recursive partitioning algorithm for building a decision tree is rather intuitive. The data is divided multiple times using predictor values, which decompose the data into relatively homogeneous segments. There are various top–down decision trees inducers such as ID3 [48], C4.5 [49], CART [50]. Some consist of two conceptual phases: growing and pruning (C4.5 and CART). Other inducers perform only the growing phase. Detailed algorithms for implementing decision trees can be found in [51].

2.2.2. Support Vector Machines

Support Vector Machines (SVM) is a set of supervised learning methods used for classification and regression analysis. The main idea of the method is to construct a hyperplane that separates the sampled objects in an optimal way. The algorithm works under the assumption that the greater the distance (gap) between the dividing hyperplane and the objects of the shared classes, the smaller the average error of the classifier [52]. The advantages of the method are as follows:

- SVM method is effective in large spaces;
- It is effective if the number of measurements exceeds the number of samples;
- It uses a subset of the training set in the decision function (called support vectors), so it is also memory efficient;
- Versatility: different kernel functions can be specified for the decision function. Common kernels are provided, but one can also specify his own kernels. The disadvantages of the method include:
- If the number of features is much larger than the number of samples, overfit should be avoided when choosing kernel features, and the term regularization is critical;
- SVMs do not provide direct estimates of probabilities, which can be calculated using an expensive five-fold cross-validation.

2.2.3. *K*-Means Method

The *K*-means method is one of the commonly used clustering methods [53]. The algorithm splits the set of elements of the vector space into a predetermined k clusters. It divides the data into k clusters by minimizing the sum of the squared distances of each object to the mean of its assigned cluster. The main idea is that at each iteration the center of mass for each cluster obtained in the previous step is recalculated, then the vectors are divided into clusters again in accordance with which the new centers is closer according to the chosen metric. The algorithm ends when at some iteration there is no change in the intra-cluster distance in a finite number of iterations, since the number of possible partitions of a finite set is finite, and at each step the total standard deviation decreases, so looping is impossible.

2.2.4. Self-Organizing Maps

Self-organizing maps (SOM) are one of the varieties of neural network algorithms [54]. The main difference between this technology and neural networks trained by the back-propagation algorithm is that the teaching method is unsupervised, that is, the training result depends only on the structure of the input data. The algorithm for the functioning of SOM is one of the options for clustering multidimensional vectors. An example of such algorithms is the *k*-means algorithm. An important difference of the SOM algorithm is that in it all neurons (nodes, centers of classes) are ordered into some structure (usually a two-dimensional grid). During training, not only the winning neuron is modified, but also its neighbors, but to a lesser extent. SOM can be considered as one of the methods for projecting multidimensional space into space with a lower dimension. When using this algorithm, vectors that are similar in the original space turn out to be nearby on the resulting map.

3. Experimental Results

3.1. Exploratory Data Analysis and Visualization

We use qualitative and quantitative indicators about social characteristics of personnel (education, marital status, children), anthropometric (gender, age) and characteristics of self-assessment of the state and quality of personnel health (current health problems; chronic diseases; health self-assessment; proper nutrition; bad habits), Table 1.

Table 1. Indicators, variables and range of variable values.

Indicator	Variable	Variable Value or Binary
Age	age	20–65
Gender	gender	female (0), male (1)
Marital status	mar	Not married (0), married (1)
Education	edu	Specialized secondary (0), higher (1)
Children	child	0, 1, 2, ...
Chronic diseases	chron_dis	no (0), yes (1)
Feeling unwell	bad_healh	Infrequently (0), often (1)
Self-reported health as weak and unsatisfactory	health_self-ass	no (0), yes (1)
Inadequate nutrition	nutr	no (0), yes (1)
Bad habits	bad_hab	no (0), yes (1)
Individual labor productivity	labor_pert	136–420 rub (1 ruble is equivalent to 0.01 euro) per hour

The transition of the qualitative values into quantitative ones is carried out on the basis of binary coding (0 and 1), while the quantitative value of a feature increases with its qualitative characteristics intensifies. Individual labor productivity is calculated using the methodology that is used to assess the labor productivity of companies in the basic non-resource sectors of the economy [55]. Within this methodology labor productivity reflects the measure of value added per employee of the company. We receive all data by the special employees' survey with using the developed questionnaires.

Whiskers diagrams visualize the expected impact of qualitative features on labor productivity (LP), Figure 2.

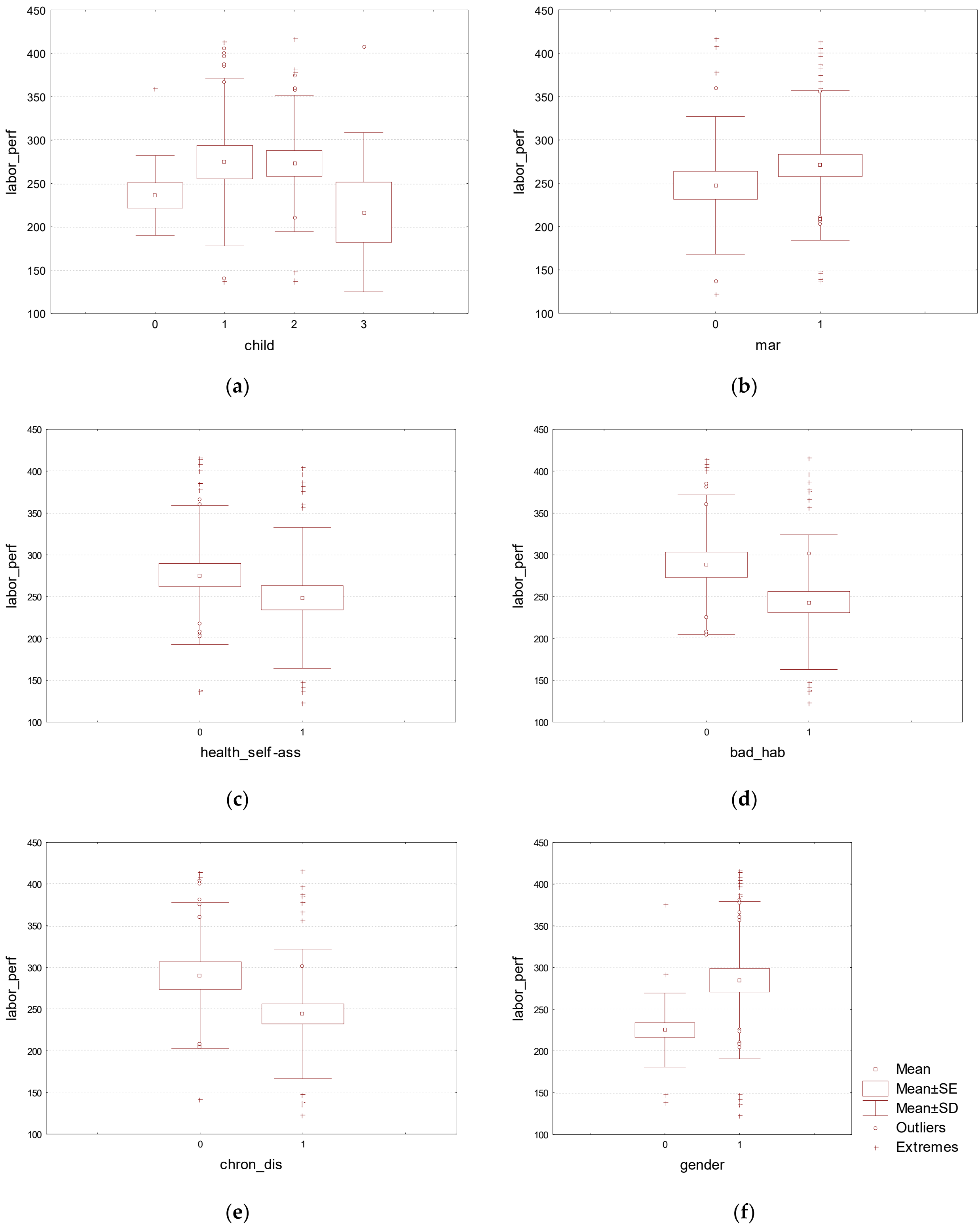
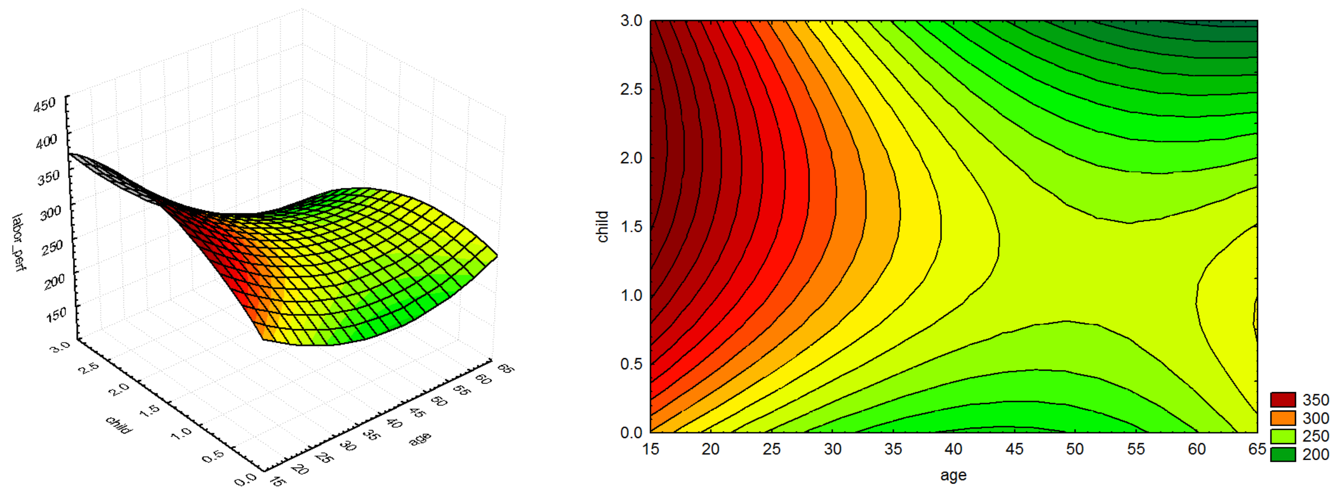


Figure 2. Whiskers diagrams for the factor groups "child and labor_perf" (**a**), "mar and labor_perf" (**b**), "health_self-ass and labor_perf" (**c**), "bad_hab and labor_perf" (**d**), "chron_dis and labor_perf" (**e**), "gender and labor_perf" (**f**).

Diagrams show that different levels of the factors gender, child, health_self-ass and bad_hab determine the difference in the labor productivity indicator—labor_perf. Thus, men have higher average labor productivity, about 280 rubles per hour than women—225 rubles per hour. Those personnel who do not have chronic diseases do not often feel unwell and do not have bad habits; their average level of labor productivity is higher than others.

Workers with one or two children have more stable level of labor productivity, close to the average, which, in turn, is higher than workers without children.

3D surface plots and contour plots for visualization of labor productivity (labor_perf) depending on the quantitative variables (age) and (child) are shown in Figure 3. From these visualizations, it's obvious that younger workers under the age of 35 with children have higher levels of labor productivity than older workers (over 55 years old) with more than three children, as well as middle-aged workers (from 35 to 55 years old) without children.



(**a**) (**b**)

Figure 3. 3D surface plots (**a**) and contour plots (**b**) for the variable "labor_perf" depending on variables "age" and "child".

Descriptive statistics for the variable "labor productivity" characterize the significant variation, non-coincidence of indexes—mean, mode, median and variation demonstrate data heterogeneity, Table 2.

Table 2. Descriptive statistics for the LP variable.

Index	Value	Index	Value
Mean	262.7	Minimum value	123
Mode	208	Maximum value	416
Median	231.5	Standard deviation	84.2
		Variation	0.36

Correlation analysis identifies paired relationships between studied factors and labor productivity. We also note that surveyed indicators were measured on different scales. Labor productivity, age and number of children have a continuous metric scale, education level has an ordinal (rank) scale and other indicators have on a nominal, categorical scale. Therefore, the analysis of these factors' interrelationships in order to identify their significant influence on the modeled indicator—labor productivity—is to carried out using different metrics. So, to measure the relationship between labor productivity, age and the number of children, we use the Pearson correlation coefficient, to assess the effect of education level on labor productivity we calculate Spearman's rank correlation coefficient, and to assess the influence of categorical variables on labor productivity we apply multivariate analysis of variance.

Using multivariate analysis of variance (ANOVA) we test the hypothesis about the equality of the mean values for the corresponding levels of factors pairs (labor productivity and the presence of chronic diseases, labor productivity and gender, etc. for all seven dichotomous variables). We tested hypothesis of equality of mean values and this hypothesis is rejected for three factors—"gender", the presence of chronic diseases ("chron_dis") and the presence of bad habits ("bad_hab"). For the other five factors, this hypothesis is accepted, since the calculated values of the Fisher's *F*-test are less than the tabular value at a significance level of 0.05. Thus, the factors "gender", "chron_dis" and "bad_hab" are significantly associated with labor productivity "labor_pert", while the other four factors do not have a statistically significant effect on it.

Estimation of the Pearson coefficient for pairs of age—labor productivity and children—labor productivity has shown that age has a statistically significant inverse effect of its average strength on labor productivity (Pearson's correlation coefficient is about 0.32), and the children does not have any significant impact on labor productivity (the calculated value of Student's *t*-test is less than the tabular value at a significance level of 0.05). Calculation of Spearman's correlation coefficient to assess the influence of education on labor productivity showed that these factors are not correlated, which contradicts the generally accepted thesis that the quality of an employee's education contribute to the growth of his labor efficiency. To exclude false correlations, we construct a matrix of partial correlations, Table 3.

Table 3. Partial correlations of factors (significant parameters are marked in red).

Variable	Age	Gender	Mar	Edu	Child	Chron_ dis	Bad_ healh	Health_ self-ass	Nutr	Bad_ hab	Labor_ pert
age	1.00	−0.23	0.06	−0.22	0.30	0.35	−0.01	0.18	0.17	0.20	−0.32
gender	−0.23	1.00	0.20	0.07	0.03	0.04	0.18	−0.03	−0.10	0.01	0.34
mar	0.06	0.20	1.00	0.07	−0.00	−0.02	0.18	0.09	−0.04	0.07	0.03
edu	−0.22	0.07	0.07	1.00	−0.08	−0.28	−0.00	−0.05	0.00	−0.15	0.02
child	0.30	0.03	−0.00	−0.08	1.00	0.13	−0.14	0.20	0.13	0.26	−0.02
chron_dis	0.35	0.04	−0.02	−0.28	0.13	1.00	0.26	0.26	0.25	0.77	−0.27
bad_healh	−0.01	0.18	0.18	−0.00	−0.14	0.26	1.00	0.48	0.21	0.31	0.02
health_self–ass	0.18	−0.03	0.09	−0.05	0.20	0.26	0.48	1.00	0.54	0.41	−0.31
nutr	0.17	−0.10	−0.04	0.00	0.13	0.25	0.21	0.54	1.00	0.18	−0.20
bad_hab	0.20	0.01	0.07	−0.15	0.26	0.77	0.31	0.41	0.18	1.00	−0.25
labor_pert	−0.32	0.34	0.03	0.02	−0.02	−0.27	0.02	−0.31	−0.20	−0.25	1.00

The table shows that variables as "age", "gender", "chron_dis" and "bad_hab" affect labor productivity (significant correlations are marked in red). In addition, close partial correlations are observed between factors "chron_dis" and "bad_hab", "bad_hab" and "health_self-ass", "bad_hab" and "bad_healh", "nutr" and "health_self-ass" also between a pair of factors "chron_dis" and "age". This explaine an existence of poor nutrition, bad habits cause chronic diseases and poor health.

At the next stage we test several different specifications regression models. The modeling takes into account different predictors scales as well as their multiple correlations. Modeling results for the best model are given in Table 4. The regression model includes a set of predictors, in that number multiplicatively related predictors that have linear correlations with the modeled variable—labor productivity.

The model gives an idea of the quantitative influence of the selected predictors on labor productivity. The combined effects of factors especially increase their negative influence. Thus, such factors combination as the frequency of feeling unwell and the presence of bad habits reduces labor productivity as much as possible (on average by 477 rub/h). The presence of chronic diseases and the self-assessment of one's health are not strong enough reduce labor productivity by an average of 449 rubles per hour, and in married men this effect increases by another 162 rubles per hour. Furthermore, in sample of married men with chronic diseases there is a decrease in labor productivity by an average of 584 rubles per hour. We also mention that there are some shortages of the described regression model. Firstly, some of its parameters are statistically insignificant, and secondly, many qualitative predictors negatively affect the results of model interpretation, as well as interpretation complexity.

Table 4. Regression results for labor productivity modeling (only significant regressors are included).

Predictor (Regressor)	Regression Coefficient	Regression Coefficient Error	T-Statistics	*p*-Value
age	−5.232	2.2219	−2.35490	0.028854
mar*chron_dis	−584.479	120.7443	−4.84064	0.000099
gender*bad_healh	254.329	76.3480	3.33118	0.003329
mar*bad_healh	111.577	49.7048	2.24479	0.036250
edu*bad_healh	121.695	55.9648	2.17450	0.041843
chron_dis*bad_healh	560.109	103.1680	5.42909	0.000026
gender*health_ass	−229.364	78.0956	−2.93696	0.008152
edu*health_ass	−108.392	43.4358	−2.49546	0.021441
chron_dis*health_ass	−488.851	105.3426	−4.64059	0.000158
mar*bad_hab	516.338	108.2071	4.77176	0.000116
chron_dis*bad_hab	578.543	141.1459	4.09890	0.000558
bad_healh*bad_hab	−476.916	95.9670	−4.96958	0.000074
health_ass*bad_hab	346.146	66.1466	5.23302	0.000040
gender*edu*bad_healh	79.240	34.3925	2.30400	0.032080
gender*mar*health_ass	−162.445	62.3059	−2.60721	0.016862
gender*edu*health_ass	−84.053	34.6773	−2.42387	0.024960

3.2. Clustering and Classification of Companies' Employeers

In order to smooth out the identified data inhomogeneities, as well as to order complex factors interactions we design the technique for dividing personnel into homogeneous groups. This provides a detailed data study and identify patterns in the obtained homogeneous groups. For these we examine various methods.

Clustering has two stages—qualitative analysis using hierarchical methods and analysis using the *k*-means method [56–58]. Analysis of various partitions of the original sample by the method of hierarchical classification showed that it is possible to form from three to six clusters. For the more reasonable grouping of objects (personnel), we use *k*-means clustering method with quantitative criteria to assess the clusterization quality. Table 5 shows the clustering results.

Table 5. Clusters' centers (*K*-means method).

Variable	Average Value of the Variable in the Cluster			
	1	2	3	4
age	34.7	46.3	35.6	33.1
gender	1	0	1	0
mar	1	1	1	0
edu	1	1	0	1
child	1	2	2	0
chron_dis	0	1	1	0
bad_healh	0	1	1	1
health_self-ass	0	1	0	1
nutr	0	1	0	1
bad_hab	0	1	1	0
labor_pert	301.6	221.4	290.8	227.8
cluster size	191	229	184	98

The most numerous cluster (229 employees) is the second, including for about a third of all respondents. These are mostly married women with higher education, above average age with two or more children. Employees in this cluster have significant health problems, some of them have chronic diseases, bad habits and at the same time, have the lowest labor productivity in the sample.

The first cluster includes mainly married men with higher education, having one child, taking care of their health, has good nutrition and no health problems. The average age of workers in this group is 34.7 years; their average individual productivity is quite high, equal to 301.6 rub. per hour. Employers in this cluster can be designated as "healthy" and do not require special decisions about their health by the company. The third cluster includes 26% of all respondents consist of mainly men with secondary education and two children, they rate their health not very high, they have irregular meals and often have seasonal diseases along with chronic diseases. The fourth cluster is about unmarried women with higher education, who do not have children and bad habits, and they characterize their health as quite satisfactory.

To select the most effective methods for the employers' clustering and then classification by the health quality in order to increase labor productivity, we compare the effectiveness of different statistical and machine learning methods and then choose one with the maximum quality value [59–64]. For this we solve two subproblems:

- Clustering an employers to form homogeneous groups with similar labor productivity profiles. For this we test two clustering methods—*k*-means method and neural network method based on self-organizing Kohonen maps (SOM);
- Classification an employers to identify the performance profile of the new employee, or to determine the cluster to which he is more likely to belong. At this stage we use the following methods: decision trees and support vector machines.

Results of the first subproblem decision. In the clustering problem the number of clusters is not known in advance and the personnel sample is rather heterogeneous. Therefore, to obtain adequate division into clusters, we use another machine learning method—Automated Neural Networks (ANN) based on SOM. Then we compare the effectiveness of two methods for obtaining personnel clusters—*k*-means method and ANN method.

To obtain the number of clusters we use the Self-organizing Kohonen map—a neural network with unsupervised learning. We divide the initial data set into three subsets—the first is a training sample in the amount of 70% of the total sample, which is used to train the neural network and adjust its weights. The second subsample is a test one, is about 15% of the total sample, it is used to check the training and retraining. The third subsample, the validation sample, is used to assess the neural network accuracy on a "new data". First, the topological dimension of the network is set to 25 neurons (the matrix has a dimension of five rows and five columns). As simulation result, it was shown that four clusters can be clearly distinguished, since it was precisely four neurons that described most of the initial data. The clustering results obtained on the basis of the ANN method is shown in Table 6.

Table 6. Clusters' centers (ANN-method).

Variable	Average Value of the Variable in the Cluster			
	1	**2**	**3**	**4**
age	34.2	34.1	41.0	41.7
gender	1	0	1	1
mar	1	1	1	0
edu	1	1	1	1
child	1	1	2	2
chron_dis	0	0	1	0
bad_healh	0	1	1	1
health_self-ass	0	1	1	0
nutr	0	1	1	0
bad_hab	0	1	1	1
labor_pert	294.12	287.35	224.46	265.26
cluster size	170	142	241	149

The clustering results are similar to the result of cluster analysis based on *k*-means. For a more reasonable choice one of the clustering methods and obtaining homogeneous personnel groups we conduct an analysis of used methods robustness. For this, an additional quantitative variable was introduced into the data set, reflecting the number of days spent by an employee on sick. Further, taking into account this new factor, new clustering is formed. Clustering based on *k*-means showed higher stability of groups in terms of their identical composition before and after the introduction of a new factor than the ANN clustering. Therefore, for clustering it is most expedient to use the *k*-means method.

Results of the second subproblem decision. Two classification models are compared. The first model uses a machine learning algorithm based on growing decision trees (boosted trees), and the second model uses the Support Vector Machines (SVM). The classification quality is estimated by the number of correct predictions—the cluster to which the employee belongs in the test sample. Thus, in the model based on boosted trees 96.4% of correct predictions were obtained, and in the SVM method only 89% of correct predictions were obtained. It is shown that the boosted trees method under many categorical predictors show higher accuracy when predict the class (labor productivity profile) of a new employee. The SVM method is most suitable for forecasting when there are many quantitative predictors.

4. Discussion of Results: Management Decisions to Improve Employers' Health Quality

On the next stage of the proposed technology, we examine different regression models of the investigated predictors (regressors) on labor productivity for each constructed cluster. The regression models quality (with a different composition of regressors) corresponding to each cluster is tested and the best ones were selected in terms of quality criteria—maximum determination coefficient (R^2) and minimum moving average approximation error (MAPE). Designed models give a clear idea of the different factors impact on the modeled indicator (labor productivity) and allow making predictions about the factors changes impact on labor productivity, Table 7.

Table 7. Regression results by employees' clusters (significant parameters are marked in red).

Predictor (Regressor)	Regression Coefficient for Models, Different by Employees' Clusters 1	2	3	4
age	2.2938	−3.4964	2.4323	−0.3619
child	−3.8365	−5.6638	−6.5767	−76.8798
gender	−3.8608	37.5001	−0.7216	−40.0442
mar	16.3362	−24.5735	38.9882	−22.7630
edu	−9.5457	83.0892	−0.3464	29.0374
chron_dis	−23.6031	38.1560	−0.7990	−5.0536
bad_healh	15.9159	105.3204	−20.1630	−40.0442
health_ass	−30.3469	139.8367	23.9315	−40.0442
nutr	−13.0980	136.2081	−12.1418	26.6200
bad_hab	−23.6031	−80.6174	−3.4200	−46.6946
Regression intercept	139.0025	249.9718	109.6893	460.2615
R^2	0.84	0.73	0.71	0.76
MAPE	10.3	16.6	12.1	11.6
F-test	4.1	4.1	4.6	4.3

Some intercepts in the models are significant for the significance level of 0.05. It means that there are some other predictors for labor productivity modeling such as qualifications level, work experience, possession of the required competencies, production automation and digitalization level etc. The designed models for the analysis and forecasting of employees' labor productivity by their special cluster are totally statistically significant and permit the prediction of labor productivity with a high accuracy, since minimum moving average approximation errors are from 10.3% to 16.6% for different models. These models are used to predict labor productivity under various scenario options for influencing factors about health quality.

For obtaining beneficial effects for business, the idea of a healthy lifestyle and a management system aimed at preserving the employees' health has a number of significant functions. First, it is a motivational function. An investment into employees' health, which is accompanied by certain measures and actions, is an element of the corporate social responsibility system. The existence of the social package for employees is an indicator of a companies' status and its reputation. These increase employees' loyalty to the company and are strategically important to their motivations. Secondly, a company development strategy is an element of its corporate culture. Healthy lifestyle ideas adopted by employers become part of the informational internal corporate environment and have a great team-building effect.

Organization of a set of management decisions to employees' health preserve is based on the following activity types: socio-psychological, financial-economic and material-technical. Activities related to socio-psychological factors provide employees' values orientations, motivation for a healthy lifestyle, training and creation of a favorable moral and psychological climate and an atmosphere of team cooperation, development and implementation of a recreational activities system. Pedagogical tools are used here. Measures focused on financial and economic conditions include ensuring the required costs for material incentives to health-preserving activities. Measures that ensure the material and technical conditions for health preservation include the development of the material and technical base, physical culture and sports events, organization of a psychological relief room.

Employees' homogeneous groups received at the previous stage of the technology, have meaningfully different labor productivity profiles and health status. Therefore, we apply differ management decisions (strategies) for control labor productivity by preserving health quality. Such strategies are developed for four homogeneous clusters characterizing the health status of workers as excellent, good, satisfactory and bad. For each employee's group we propose its own strategy—current control, monitoring and prevention, healthy lifestyle prevention and strong involvement, Table 8.

Table 8. Management decisions (strategies) for improving employee's health quality by their groups.

Cluster	Employee Profile, Reflecting Health Status	Health Improvement Strategy	Management Decisions
1	Excellent	Current control	Regular conversations, trainings
4	Good	Monitoring andprevention	Trainings and monitoring the employees' health
2	Satisfactory	Healthy lifestyle prevention	Regular monitoring and implementation of measures to improve health status
3	Bad	Strong involvement	Regular implementation of activities—promotion of a healthy lifestyle; mass sports; regular spa treatment; wellness programs

We conduct an efficiency assessment for development and implementation of listed strategies. The economic effect for implementation of management decisions is ensured by: reducing the number of technological violations committed by personnel; reduction of sick leave payments, reduction of sick leave; reduction of days of works' incapacity; increasing the quality of work performed, Table 9.

Table 9. Costs assessment before and after management decisions implementation.

Cost Item	Cost Value before Management Decisions Implementation, Rub.	Cost Value after Management Decisions Implementation, Rub.	
		Optimistic Option	Realistic Option
Cost for sick leave	366,125	0	124,593
Cost for the replacement of absent employee	2,295,625	0	1,023,500
Tolal cost	2,661,750	0	1,248,093

For example, the strategy "Strong involvement", developed for the employees in the third cluster, which is about one third of the total sample, includes the following activities: promotion of a healthy lifestyle; mass sports; expanding the list of working specialties provided with regular spa treatment; development of health-improving programs. Total investments for this strategy implementation are 260,000 rubles. The economic effect sources of the proposed program are:

- Reducing a cost of sick leave. Since the employees in the third cluster make 34 percent of all employees, we accept two options: an optimistic one, which results in a complete reduction in the incidence of sickness among employees in this cluster, and in the second realistic option, a reduction in the incidence and costs of sick leave payments is ensured by 20%;
- Reducing a cost of replacing an employee who has left for sick leave. Similarly, to assess the effect, an optimistic option is considered, in which these costs are completely eliminated, and a realistic option, in which the cost reduction will be 20%.

The company costs associated with the absence of an employee due to illness will decrease by more than 1,413,000 rub., and the net savings, taking into account the costs of implementing the programs, will amount to more than 1,153,000 rub. Labor productivity for the company, calculated separately for the employees of this cluster, after management decisions implementation, will amount to 6,509,000 rubles per person, which is 2% higher than the initial value.

We also note that as a result of management decisions implementation to preserve an employees' health, there are also social effects associated with motivation increasing and higher satisfied employees with their health quality, which in turn is contribute to labor efficiency growth.

This suggested technology can be used by other companies by different ownership forms and size. The direction of technology improvement could include the factor of "production type"– labor-intensive or capital-intensive, since it affects the elasticity of resource replacement, which is important in the context of economy digital transformation.

5. Conclusions

We have tested and accepted as a correct hypothesis about the need to take into account human health factors as a productive resource of the economy when managing this resource productivity. It is shown that really factors describing the state and quality of human health affect the quality and labor efficiency.

This work is aimed at providing decision making support for manage of planned projects to increase labor productivity and a company performance growth with using data science methodology. To form a computer programs package that decides this problem, it is necessary to determine a set of algorithms and methods used. The search for effective algorithms and methods is the content of this work. Based on the results obtained, system analysts and top managers acquire appropriate toolkits to integrate it into the enterprise management information system.

It is shown that for a more comprehensive description of labor productivity as a controlled object in addition to economic factors, it is necessary to process social, demographic factors and factors about health status of personnel. Using methods of correlation and regression analysis it was found that significant determinants of labor productivity are indicators of personnel health state and health quality.

In order to make decisions about labor productivity management an integrated approach is worked out that systematically describes the patterns of marked factors influencing labor efficiency and sets up adequate management decisions. Under suggested approach many different factors are selected and substantiated on the basis of their correlation on labor productivity. Further the personnel clustering and designing of their homogeneous groups having similar values of demographic, social factors and health quality characteristics are carried out. Then typical personnel profiles are designed that is the basis for development different strategies and management decisions applicated for employees in each cluster separately.

It is proved that to solve the problem of clustering and forming personnel homogeneous groups, it is most expedient to use the *k*-means method, which is more reliable than the clustering based on Kohonen's neural networks. Over problem of classification and prediction a profile of a new employees, featured by many qualitative variables, such as gender, education and a qualitative self-assessment of health, the method based on the boosted trees algorithm is demonstrated higher efficiency.

The developed technology for labor productivity management has been tested and implemented at one of the enterprises of the electric power industry. We proposed management decisions and the following results have been achieved: the enterprise costs related to the incidence of sickness of workers decreased by more than 70%, labor productivity increased by 2%, which ensured an increase in the company's revenue of about 8%.

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Appendix A

Table A1. Health Self-Assessment Questionnaire.

Question Number	Question	Answer	
		Yes	No
1	Does headache bother you?		
2	Do you easily wake up from any noise?		
3	Are you worried about pain in the heart?		
4	Do you think that your eyesight has deteriorated?		
5	Do you think that your hearing has deteriorated?		
6	Do you try to drink only boiled water?		
7	Do the younger ones give way to you in public transport?		
8	Do joint pain bother you?		
9	Does the change in the weather affect your well-being?		
10	Do you have periods when you lose sleep because of anxiety?		
11	Are you worried about constipation?		
12	Are you worried about pain in the liver (in the right hypochondrium)?		
13	Do you have dizziness?		
14	Has it become more difficult for you to concentrate now than in past years?		
15	Are you worried about the weakening of memory, forgetfulness?		
16	Do you feel a burning sensation, tingling sensation, "creeping creeps" in various parts of your body?		
17	Do you have noise in your ears?		
18	Do you keep one of the following medicines at home: validol, nitroglycerin, heart drops?		
19	Do you have swelling in your legs?		
20	Did you have to give up some of the dishes?		
21	Do you have shortness of breath when walking fast?		
22	Are you worried about lower back pain?		
23	Have you ever used any mineral water for medicinal purposes?		
24	Is it possible to say that you have become whiny?		
25	How often do you drink alcoholic beverages?		
26	Do you think that you have become less efficient than before?		
27	Are the periods when you feel joyful, excited, happy disappeared in your life?		
28	How do you assess your state of health (good, satisfactory, bad or very bad)?		
29	Do you often get colds and flu?		
30	Do you smoke?		

Table A2. Correspondence Between Questionnaire Questions and Summary Indicators to be Further Processed in the Technology.

Indicator	Characteristic	Question Number in the Questionnaire
Chronic diseases	Diseases that can be controlled but not completely cured	3,8,11,16,19,21,22,29
Feeling unwell	An employee health state, which does not allow them to fully carry out his labor activity	1,9,10,13,14,17,27
Self-reported health as weak and unsatisfactory	An employee's overall assessment of his health	2,4,5,7,15,18,24,26,28
Bad habits	Habits that negatively affect employee health	12,25,30
Inadequate nutrition	Food that eliminates harmful or useless substances in the diet	6,20,23

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