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Stacking Machine Learning Model for the Assessment of R&D Product's Readiness and Method for Its Cost Estimation

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Abstract: The modern technology universities have the necessary resource and material base for developing and transferring R&D products. However, the cost estimation process is not formalized. There are many methods of estimating the cost of R&D products' commercialization processes. However, in some cases, we cannot consider any single technique to be the best one as each of them has advantages and disadvantages. In such conditions, all efforts should be made to use a combination of the estimation techniques to arrive at a better cost and quality estimate. The effectiveness of the valuation of R&D products is of particular importance in today's economy and due to the need to analyze large data sets prepared for transfer from universities to the business environment. This paper presents the model, two methods, and general information technology for R&D products' readiness level assessment and R&D products' cost estimation. The article presents the complex method for determining the cost of R&D products, which will allow: increasing the efficiency of the transfer, commercialization, and market launch of R&D products, and promoting the interaction of all components of the national innovation infrastructure, innovations, etc. The need to consider many different indicators when evaluating R&D products has determined the need to use machine learning algorithms. We have designed a new machine learning-based model for the readiness assessment of R&D products, which is based on the principle of "crowd wisdom" and uses a stacking strategy to integrate machine learning methods. It is experimentally established that the new stacking model based on machine learning algorithms that use random forest as a meta-algorithm provides a minimum of a 1.03 times higher RMSE compared to other ensemble strategies.

Keywords: R&D product; machine learning; ensemble; cost estimation; readiness level

MSC: 41-02

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1. Introduction

The rapid pace of technological development in the world, due to the influence of the IV Industrial Revolution and the globalization of the world economy, identified the need to produce new approaches to managing the generation, transfer, and commercialization of R&D products and their economic evaluation. The shortening of the innovation life cycle and the spread of market effects from R&D products (spillover, convergence, diffusion, etc.) indicate that the product should be evaluated not only when it is ready but also in the initial stages of readiness. In particular, the economic evaluation of an R&D product at the idea stage can help predict product development and answer questions about the technical practicability of the further development of this product and the economic meaning of its market launch [1]. However, the lack of existing methodological support for the transfer and commercialization of R&D products based on their readiness does not allow market demands for R&D products to be met quickly.

At the same time, the active promotion of the paradigm of open innovation [2,3] by the community of developed countries has contributed to the fact that the crucial role in the processes of the transfer and commercialization of R&D products belongs to universities [4,5]. For the most part, modern technology universities have the necessary resource and material base for developing and transferring R&D products, technology transfer centers, etc. Based on the efficient transfer and commercialization of R&D products, universities can ensure the country's long-term technical and economic growth. The importance of the above is evidenced by the conclusions set out in many analytical documents of the World Economic Forum (WEForum, 2020–2021).

This highlights the need to create methodological support for the transfer and commercialization of R&D products based on their readiness, from universities to the environment. An essential task of the effective development of evaluation methods and models for R&D products is to consider both the peculiarities of the readiness of technologies and the market considered for their commercialization.

In our opinion, a practical approach to the economic evaluation of product R&D based on its readiness is to create a model that contains a system of interactions between the key indicators of the readiness and the market perception of the product. Such interactions are characterized by a complex level of correlation, which depends on internal factors (the process of product development at the university) and external (state, trends, and market development patterns). The model of such an assessment is designed to answer questions about: the range of possible product prices, market launch scenarios, and the type of market coverage strategy, diffusion, and market behavior of the product, and so on. These and other economic categories should be determined by methods that are organically combined in this model.

From a scientific and practical point of view, R&D products' readiness, as a basis for estimating their value, is the subject of much debate. Several researchers in the field [6,7] consider readiness from the technological maturity of products. Others [8–10] propose substantiating the readiness indicator by modeling the achieved level of satisfaction of R&D products with market needs (marketing, legal, social readiness, etc.). There are methodological approaches to determining the readiness of R&D products as objects of intellectual property rights [11,12]. Each of these approaches is designed to establish the level of readiness of the R&D product in specific market conditions and a certain period of economic evaluation.

However, virtually none of the current developments reflect the relationship between the availability and cost of R&D products. It causes significant difficulties during their transfer from universities to the business environment and further commercialization. Taking into account the level of readiness during the valuation allows you to justify the price of R&D of the product. For example, the readiness of the product at low levels (idea, product concept, etc.) will lead to a lower cost of the R&D of the product compared to its readiness at high levels (prototype, production preparation, etc.). From a market standpoint, the higher the product's technological readiness level, the lower its transfer and commercialization risk.

An economic evaluation of product R&D, aimed at maximizing the various factors that take place in its development and taking into account the cost–income indicators of product R&D, is relevant in much of the work of scientists and practitioners. There are different points of view and solutions to this problem. For example, an R&D product's assessment can be performed to achieve a set of objectives. Thus, the program and the evaluation mechanism are considered strategic tools for improving activities' efficiency [13]. Evaluation objectives may include:

- communication studies between R&D spending and the market price of Thai corporate common share [14];

- to explore the strategic entanglements of financial models for managing R&D and building a firm's competitiveness [15];
- to investigate the relationship between manufacturing–R&D integration and organizational culture in improving quality and product development performance [16];
- to obtain fitter decisions concerning risk reduction and further assist them in reaching higher performances in R&D partnership risk management [17].

In [18], under the ICAPM framework, the authors have proposed that an R&D factor is a proxy for innovations to a state variable.

However, the existing methods that take into account cost and revenue do not always provide satisfactory results regarding the desires of the dynamic market. In particular, the current developments of scientists and practitioners in economics and related fields have not solved these problems:

- the relationship between the cost of product R&D and such essential elements as the level of its technological readiness (TRL), analytical readiness (ARL), consumer readiness (CRL), and patent readiness (PRL);
- creation of a basis for the development of R&D of the product's commercialization scenarios under different conditions of its readiness and transfer options;
- development of an intellectualized approach to product R&D evaluation, which can take into account both product features and the specifics of the market environment.

The considered difficulties cannot be solved purely analytically. Such tasks require a thorough formalized, algorithmic, and programmatic rationale, which involves establishing relationships between R&D product indicators and their level and nature. At the same time, a significant difficulty is the economic evaluation and combination of value and cost indicators in one system. It should also be borne in mind that the synergistic nature determines the value of the R&D product: the specific level of readiness is taken into account; each component should affect at this level the total cost of the product with a certain weight. At the same time, the combined effect of these components will have a significantly greater impact than each component alone. The importance of considering these elements in evaluating the R&D of the product necessitates the development of new practical tools that can ensure that evaluators obtain adequate results.

The solution to this problem can be considered based on the application of machine learning algorithms. That is why the possibility of using machine learning methods for R&D products' evaluation is analyzed.

The authors in [19] use the Bayesian belief network model for the prediction of an R&D project's success. They built a risk quantification model and used it for the prediction of the failure risk probability of R&D projects.

In paper [20], biopharmaceutical R&Ds only are taken into account. The authors formed 123 key R&D risks and grouped them into five R&D value chain segments and 27 respective process domains.

The Cronbach alpha reliability test is used in the paper [21]. In addition, a multiple regression model is built. The paper [22] presents an approach for a customer-perceived value investigation using the structural equation model and opinion mining.

The authors in [23] focused on software cost estimation. They used an empirical approach for this. However, the mentioned method cannot be used for other R&D evaluations because it considers specific software characteristics.

Thus, the literature analysis provides a review of the current methods to estimate the cost of R&D products, taking into account the singularities of market changes and the growing strategic role of the university in the region's innovation infrastructure. The limitations of the current methods are:

(1) The models support the analysis of particular types of R&D products [20,23]. That is why they can be used only for a specific domain.

(2) The Bayesian belief network model and risk assessment [19] require numerous probability estimation datasets. It is impossible to use for universities' R&D products due to a limited number of collected surveys.

(3) Regression [21] is widely used for cost prediction. However, comparing the resulting predictive accuracy with other predictors would be interesting.

(4) Feedback analysis and opinion mining [22,24,25] are mainly used for quality evaluation. Unfortunately, for R&D product costs, initial information about possible users' feedback is usually absent.

(5) The existing studies conducted surveys with global companies and made an empirical examination [26–29]. However, there is a lack of investigations into relationships between technology commercialization capabilities, type of business, sustainable competitive advantage, sector, industry, etc.

(6) The econometrics models [30,31] can be used for R&D indicators' evaluation. They allow finding the relationship between the cost of R&D products and the level of their technological readiness. However, the biggest problem with R&D product cost estimation is that it is necessary to combine different approaches, not only parameters' estimation.

The paper aims to develop a new machine learning approach for R&D products' technological readiness estimation to provide high prediction accuracy. The level of analytical readiness, technology's influence level, developers' parameters, the direction of technology for the consumer, etc., should be considered. Moreover, the influence of different parameters on the technology readiness level and R&D product cost should be evaluated.

The main contributions of this paper are the following:

- we have collected the dataset of R&D products and their parameters based on the expert survey, which provided the opportunity to apply machine learning methodology to reduce time and resources during the assessment of readiness and cost estimation of R&D products;
- we have designed a new machine learning-based model for the readiness assessment of R&D products, which is based on the principle of "wisdom of the crowd" through the use of a stacking strategy with the ensembling machine learning methods that provides an opportunity to improve the accuracy for significantly solving the stated task;
- we have designed a comprehensive method for R&D products' cost estimation, which, by taking into account the results of the model for the readiness assessment of R&D products, as well as the availability of analogs on the market, allows us to increase the accuracy and reliability of the evaluation results through combinations of cost, revenue, and competition pricing approaches;
- we have developed intelligent information technology that provides an automatic assessment of the readiness and cost estimation of R&D products through the implementation of the above model and method, which allows for forming effective scenarios for the commercialization of such products.

The research methodology is built as follows:

1. dataset collection;
2. R&D level assessment model development for readiness level;
3. cost estimation method development;
4. results evaluation;
5. system architecture development;
6. system development and testing.

The practical value of the proposed methods and models for universities is given below:

- they provide an opportunity for university structures involved in the transfer of R&D products (technology transfer centers, science parks, startup schools, and other innovation entities) to assess the economic feasibility of the product in the early stages of its readiness, which will help reduce the level of risks in the transfer and commercialization of products;
- they apply the author's development in the educational processes of various specialties and educational and scientific programs of educational institutions;
- they promote sound pricing of R&D products based on a variety of product impact factors;

- they substantiate the strategy of transferring R&D products from universities to the business environment, strategies for their commercialization, etc.

2. Materials and Methods

2.1. Dataset Collection

The research was conducted using case study methodology, modern theories, and data analysis practices in economics (mainly using information-receptive, reproductive, morphological, and heuristic).

Dataset was collected based on pooling results. The polling place was the research laboratories at Lviv Polytechnic National University and Startup school; the polling time was 2019–2021. The sample consists of 56 respondents. Therefore, dataset instances present results of R&D products and startups.

The research tool was the survey, which consisted of 16 concerns of a substantive nature and four questions of a personal character.

The structure of dataset looks like the following (Table 1):

Table 1. Dataset description.

Attribute Title	Attribute's Value Type
Readiness	num (target attribute)
The level of analytical readiness	num
The patent level	num
The demand readiness level	num
The society impact level	num
Developer's age	int (categorical)
Influence level	int (categorical)
Wide usage level	int (categorical)
Technological complexity	int (categorical)
Area of usage	int categorical)
The part of market	int (categorical)
Novelty level	int (categorical)
Education level	int (categorical)
Scientific level	int (categorical)
Level of knowledge usage	int (categorical)
Type of scientific research	int (categorical)
Social group	int (categorical)
Direction of technology for the consumer	int (categorical)
Direction of action	int (categorical)
Value	int (categorical)
Innovative level	int (categorical)

The first four features were evaluated; the rest of the features were categorical. That is why they were transformed using one-hot encoding. In total, 256 features were taken into account.

Descriptive Statistics and Correlation Matrix Are Given in Appendices A and B.

The methodology for R&D readiness components' evaluation is presented in our previous work [32]. Dataset was divided by training set and testing set in proportion 75% and 25%, respectively.

TRL, ARL, PRL, and CRL were influenced by expert evaluation. In total, 23 experts estimated the importance of each parameter. The results show the significance of consumer readiness level considering the readiness of the technology. The higher the CRL, the more likely the successful commercialization process. The readiness level of R&D depends, in particular, on the experience of potential consumers and the possible benefits of using this product in real terms.

2.2. Assessment Model Development

Product R&D readiness assessment is performed according to expert evaluation. If an expert is alone, this may add subjectivity to such an assessment, which will further affect assessing the cost of a product [33]. This shortcoming can be remedied by the construction of a product R&D readiness assessment process by several experts [34]. Obviously, more experts provide more different opinions, which can then give a final result using majority voting. However, this approach requires much more financial cost, in particular in the form of a reward for all experts.

In general, the above approach can be considered from the point of view of Condorcet's jury theorem [35,36]. Here the majority of votes form the initial result. However, an essential condition is the independence of experts. Only in this case is it possible to achieve the desired result. To do this, you can carefully select experts, which requires a lot of time, or weigh up the examination results, with the involvement of a meta-expert, who will set the coefficients of importance for each expert from the group [37], etc.

If there are historical data, or new data as a result of the examination are collected, it can be possible to avoid both of the above shortcomings by using ensembles of machine learning [34]. This strategy assumes that different machine learning methods, or weak predictors, act as each individual expert. In addition, there is a general meta-algorithm that weighs the results obtained by all weak predictors and gives the final decision [38].

The scientific literature considers three main methods of creating ensembles—boosting, bagging, and stacking [39]. To create the most accurate machine learning-based model for solving the problem of the readiness assessment of R&D products, as a regression task, we will create and investigate the effectiveness of each of them.

In the first stage, the weak predictors were selected and trained. Multivalued linear regression, *k*-nearest neighbor classifier, and support vector machine models were built.

The primary purpose of regression analysis is to determine the relationship between a certain characteristic Y of the object and the values of x1, x2, . . . , xn, which cause the change in the variable Y. Y is called the dependent variable, and the variable effects x1, x2, . . . , xn are called factors. Establishing a model, determining the form of regression (comparison), and estimating its parameters is the task of regression analysis.

In the regression analysis, a model of the form Y = φ (X) + ε is investigated, where Y is the resulting feature, X is a factor, ε is a random variable that describes factors x from the regression line (residual variable) [21]. The regression equation is given as: y(x) = φ (x, b0, b1 . . . bp), where x is the value of X; b0, b1, . . . , bp are the parameters of the regression function φ. Thus, regression analysis is present in certain functions, parameters, and statistical-level studies.

The *k*-nearest neighbor (*k*-NN) method is a metric algorithm for automatically organizing objects. The main principle of the nearest neighbor method is that the object is assigned to the class that is most common among the neighbors of a given element. Mathematically, the classification using *k*-NN is reduced to the calculation

$$CSV_i(d_j) = \sum_{d_z \in TR_k(d_j)} RSV(d_j, d_z) \cdot ca_{iZ} \tag{1}$$

where CSV is the categorization status value of the object d_j, $Tr_k(d_j)$ is the set k of objects d_z, for which we achieve the maximum of $RSV(d_j, d_z)$, $RSV(d_j, d_z)$ (retrieval status value) is the similarity measure between training dataset d_j and object d_z, ca_{iZ} is the value of the target attribute, k is the threshold (number of objects) indicating how many similar objects have to be considered to calculate $CSV_i(d_j)$. Any similarity function, either a probabilistic or a vector measure, can be used for these purposes.

The following data prediction method is the support vector machine, SVM [33]. The mathematical formulation of the classification problem is as follows: let X be the space of objects (for example, R^n), Y be our classes (for example, Y = {−1, 1}). Specified training sample: you need to construct a function F:X→Y (classifier) that maps the class y of the object x.

The classification function F takes the form

$$F(x) = sign((w, \phi(x)) + b) \tag{2}$$

Positive certainty is necessary for the corresponding Lagrange function in the optimization problem to be limited from below, i.e., the optimization problem would be correctly defined [31]. The accuracy of the classifier depends, in particular, on the choice of the kernel.

R-squared Error (Rsquared), MAE (Mean Absolute Error), and RMSE (Root Mean Squared Error) [34] are used for prediction accuracy estimation.

The result obtained on the testing dataset is given in Table 2.

Table 2. Results of weak predictors.

Model	MAE	RMSE
Linear regression	0.1186738	0.1497206
k-nearest neighbor, n = 5	0.2039549	0.2020502
Support vector machine, Radial Basis kernel	0.105906	0.1193939

For R&D readiness level assessment, an ensemble of machine learning methods is used [35]. First, multivalued linear regression with the random forest is organized in boosting ensemble. Each time a base learning algorithm is applied, it generates a result of a new weak prediction. It is an iterative process. After multiple iterations, the boosting algorithm combines these weak results into a single strong prediction result. Random forest was used in boosting ensemble with the following hyperparameters:

- number of variables randomly sampled as candidates at each split mtry = floor(sqrt (ncol(x))) = 16,
- number of trees ntree = 500.

Parameters tuning is not used.

Since random forest based on ensemble learning requires a lot of decision trees to obtain high performance, it is not suitable for implementing the algorithm on limited computation resources. Here, we propose a boosted random forest in which boosting algorithm is introduced into the random forest. From the original random forest fit, we extract the residuals and then fit another random forest to these residuals. We call the sum of these two random forests a one-step boosted forest.

Boosted linear regression (lm) is an iterative method that starts with a base linear model and explains the model's errors through regression trees.

The results of boosting are given in Figure 1.

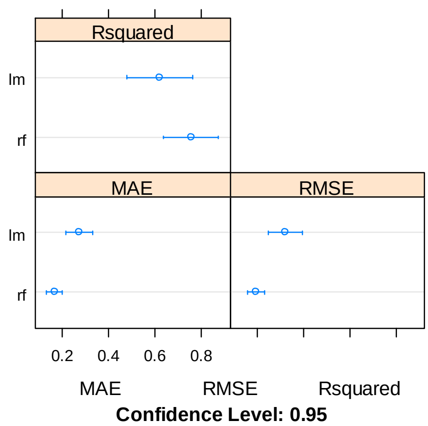


Figure 1. The predictive accuracy of boosting.

The next ensemble is bagging. A bagged regression tree (CART algorithm) and bagged random forest are built. Bagging is used with decision trees, where it significantly raises the stability of models in improving accuracy and reducing variance, which eliminates the challenge of overfitting.

Bagged random forest is an averaging method that aims to reduce the variance of individual trees by randomly selecting many trees from the dataset and averaging them.

The results of bagged models for the testing dataset are given in Figure 2. The predictive accuracy is closed to boosted rf.

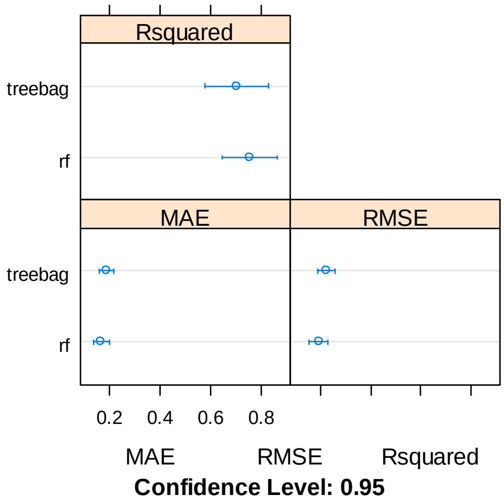


Figure 2. The predictive accuracy of bagging.

Next, we present a more promising model according to the stated task, the stacking machine learning model. Stacking is an ensemble machine learning algorithm that learns how best to combine the predictions from multiple well-performing machine learning models. A majority vote or weighing can combine basic training inputs. Additional data for retention are required if meta-learning parameters are used. It also increases the complexity of the model.

The new stacking model s_K based on machine learning algorithms that use random forest as a meta-algorithm is proposed.

The mathematical formulation of the proposed stacking is the following. We have K cross-folds randomly generated from initial dataset

$$\left\{z_1^1, \ldots z_B^1\right\}, \left\{z_1^2, \ldots z_B^2\right\} \ldots, \left\{z_1^K, \ldots z_B^K\right\}$$

where K is the number of folds, B is the size of fold, z_b^k is the b-th observation of the l-th sample.

The task is to train K independent weak regressors

$$w_1(.), w_2(.), \ldots, w_K(.) \tag{3}$$

and combine the results of training using meta-model mw

$$s_K(.) = mw(w_1(.) \times w_2(.), w_1(.) \times w_3(.), \ldots, w_{K-1}(.) \times w_K(.)) \tag{4}$$

where $w_i(.) \times w_j(.)$ is the pairwise multiplication of weak predictors' results.

The main disadvantage of the stacking model is that the meta-attributes on training and the test are different. The meta-attribute in the training sample is not the answers of a particular regressor; it consists of pieces that are the answers of various regressions (with different coefficients), and the meta-attribute on the control sample, in general, is the answer to a completely different regression, tuned to the full training. In classic stacking, situations can arise when a meta-attribute contains few unique values, but many of these values do not intersect in training and testing.

The developed stacking model also combines linear regression, k-nearest neighbors, support vector machine with radial basis function, support vector machine with a linear function as weak predictors. In addition, the meta-features are deformed based on the results of pairwise multiplication. The meta-features are the results of weak predictors' training. In the end, contorted features are used together with the training dataset in the meta-model. This combination avoids the correlation of weak predictors' results and increases the model generalization.

The general schema of the proposed new stacking model is given in Figure 3.

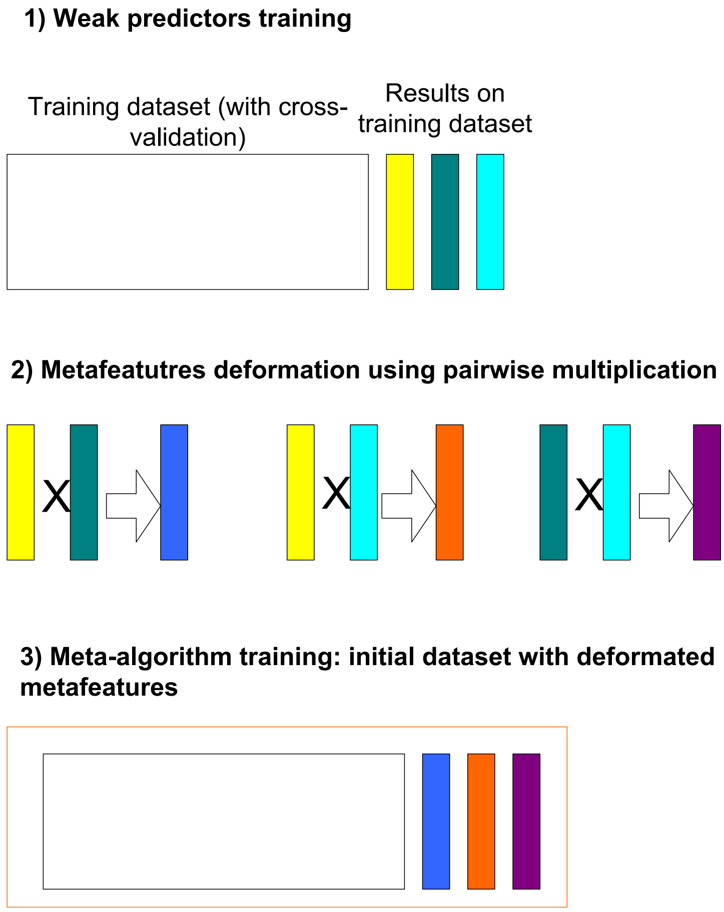


Figure 3. The stacking schema. On ox-axis, we have different colored columns: yellow, green and blue columns indicate the results made by weak predictors, dark blue, orange, violet columns indicate the results of pairwise multiplication.

The realization of the new proposed stacking ensemble is given below.

In the first step, R-squared error for weak predictors was found. R-squared error is given below (Table 3):

Table 3. The main statistical indicators of the results of weak predictors.

	Statistical Indicators					
Weak Predictor	**Min**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
rf	0.2717025×10^{-3}	0.5283736	0.8681555	0.7250325	1	1
lm	0.1335612×10^{-4}	0.2026962	0.7689927	0.5788250	1	1
k-nn	0.2583209×10^{-4}	0.5344081	0.9525670	0.7501362	1	1
svmRadial	0.2112816×10^{-4}	0.5117884	0.8886191	0.7295303	1	1
svmLinear	0.1894514×10^{-5}	0.342166	0.9491874	0.6846886	1	1

The multilayer perceptron (MLP) was used with Grid Search for hyperparameter tuning. It had two parameters to tune, the activation function, and the number of neurons in the hidden layer. Only one hidden layer was chosen due to limited dataset size.

Each example assumes that we are interested in the predictive accuracy as the metric we are optimizing, although this can be changed. Moreover, each example estimates the performance of a given model (size and k parameter combination) using repeated n-fold cross-validation, with 10 folds and 3 repeats.

Multilayer perceptron with sigmoid activation function was created with different number of neurons in hidden layer (Table 4):

Table 4. Errors values for different number of neurons in hidden layer of MLP with sigmoid activation function.

Size	RMSE	Rsquared	MAE
3	0.2223931	0.6517460	0.1977703
5	0.2449432	0.7053856	0.2065954
7	0.2710932	0.7192740	0.2174573
9	0.2611066	0.6925929	0.2084706

RMSE was used to select the optimal model using the smallest value. The final values used for the model were size = 3.

Next, MLP with hyperbolic tangent was investigated (Table 5):

Table 5. Errors values for different number of neurons in hidden layer of MLP with hyperbolic tangent activation function.

Size	RMSE	Rsquared	MAE
3	0.2286407	0.6102281	0.1943607
5	0.2073460	0.6470182	0.1766673
7	0.2074397	0.6457215	0.1767149
9	0.2088174	0.6449099	0.1760879

The final values used for the model were size = 7.

The Rsquared error for both MLPs was less than for other models. That was why MLP was excluded from possible weak predictors.

Next, weak predictors were combined at the last stage using random forest. One hundred trees were built for RF with max depth equal to 8 (Table 6). Cross-validation was also used tenfold and repeated three times. Repeated K-fold cross-validation is technically used for small datasets' validation. The advantage of this technic is the ability for parallelization.

Table 6. Random Forest result.

Number of Variables in Each Split	RMSE	Rsquared	MAE
2	0.1531979	0.6179473	0.1224977
4	0.1497206	0.5990950	0.1186738
6	0.1510873	0.5803320	0.1182399

RMSE was used to select the optimal model based on the smallest value. The final value used for the model was mtry = 4.

2.3. The Method for Cost Estimation of R&D Product

The developed model is used in the next step, particularly for R&D product cost estimation. Our previous work presents a theoretical background for cost estimation and the proposed triple model [32]. The cost estimation for the separated domains is also shown in [40–46].

This study is essential to evaluate the R&D product when concluding transfer agreements for R&D product commercialization. In general, all known factors in the traditional world approaches to pricing on R&D products can be divided into cost, revenue, and competition. The choice of valuation method depends on the characteristics of STD and valuation objectives.

Based on our previous work, the method for the cost evaluation of R&D products consists of two steps:

1. The choosing of the evaluation method.
2. The price estimation based on the chosen method or combination of methods. If more than one method is used, the possible price range is returned.

The research showed that, depending on the factors taken into account during the evaluation, it is reasonable to recommend applying one or another method for cost estimation [33]. That is why, based on the previously calculated level of readiness, the cost estimation process is organized using experts' surveys for the following parameters (Table 7). All coefficient values are chosen empirically.

Table 7. Parameters for cost estimation for R&D products.

Parameters	Rule
competitive_method.analog_implementation_costs (*Ia*)	numeric, range [0..∞)
competitive_method.analog_quality_value (*Pa*)	numeric, range (0..1]
competitive_method.analog_support_cost (*Sa*)	numeric, range [0.. ∞)
competitive_method.k1 (innovation comparison)	numeric, range {1, 1.1, 1.15, 1.2, 1.25}
competitive_method.k2 (ecological parameter)	numeric, {0.6, 0.8, 1, 1.1, 1.3}
competitive_method.k3 (complexity of implementation)	numeric, {0.6, 0.8, 1, 1.1, 1.3}
competitive_method.k4 (support complexness)	numeric, {0.5, 1}
competitive_method.k5 (attractiveness of market conditions)	numeric, (0.8, 0.9, 1, 1.1, 1.2}
competitive_method.own_implementation_costs (*Io*)	numeric, range [0..∞)
competitive_method.own_quality_value (*Po*)	numeric, range (0..1],
competitive_method.own_support_cost (*So*)	numeric, range [0.. ∞)
competitive_method.parameters_count $\sum_{i=1}^{n} q_i = 1$	array, max:5, min:1
competitive_method.analog_price (*Price_a*)	numeric, range [0..∞)
expensive_method.percentage_of_cost (*PS*)	numeric, gte:0, lte:100
expensive_method.sum.commercial_expenses ($a1$)	numeric, range [0..∞)
expensive_method.sum.defective_lose ($a2$)	numeric, range [0..∞)
expensive_method.sum.fuel_and_energy ($a3$)	numeric, range [0..∞)
expensive_method.sum.general_expenses ($a4$)	numeric, range [0..∞)
expensive_method.sum.other_production_expenses ($a5$)	numeric, range [0..∞)
expensive_method.sum.raw_materials ($a6$)	numeric, range [0..∞)
expensive_method.sum.returnable_waste ($a7$)	numeric, range [0..∞)
expensive_method.sum.social_events_deductions ($a8$)	numeric, range [0..∞)
expensive_method.sum.third_parties_production ($a9$)	numeric, range [0..∞)
expensive_method.sum.total_expenditures ($a11$)	numeric, range [0..∞)
R&D_readiness_level	numeric, gte:1, lte:11
revenue_method.discount_rate (Q)	numeric, range [0..1]
revenue_method.period.expected_cost (C)	numeric, range [1..5]
revenue_method.period.expected_price (P)	numeric, range [1..5]
revenue_method.period.licensor_percentage (Δ)	numeric, range [0..1]
revenue_method.period.sales_volume (t)	numeric, range [0..∞)

The algorithm for R&D products' cost estimation is presented in Figure 4. In this paper, we proposed to estimate the price depending on readiness level and analog availability. The minimum and maximum costs are proposed if more than one approach is used. An algorithmic implementation of this method is shown in Figure 4.

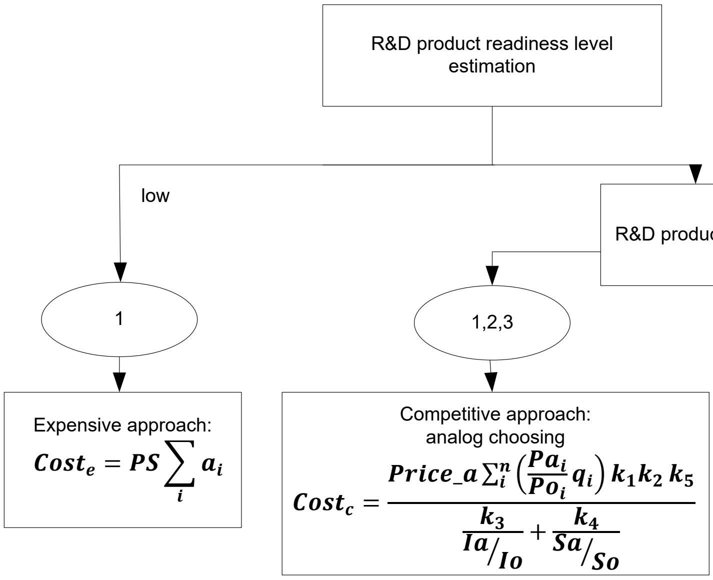


Figure 4. The proposed algorithmic realization of R&D products' cost estimation method.

3. Results

3.1. Results of Investigated Ensemble-Based Strategies for the Creation of the Model for the Readiness Assessment of R&D Products

This section presents the results of comparing ensemble methods: boosting, bagging, and stacking, created in Section 2.2, for creating a high-precision model for the readiness assessment of R&D products. The results of the comparison are given in Table 8. The new stacking model is compared with a boosted random forest, boosted linear regression, and bagged random forest.

Table 8. The comparison of the best weak predictors and ensembles.

Model	Rsquared	MAE	RMSE
New Stacking model	0.9366	0.0559359	0.05898147
Boosted rf	0.7553046	0.1640238	0.1916724
Boosted lm	0.7217016	0.2720410	0.3206452
Bagged rtree	0.7043159	0.1870193	0.2257885
Bagged rf	0.7541548	0.1662005	0.1937453

The new stacking model allows the RMSE (Root Mean Squared Error) to be decreased 1.03 times compared to other ensembling strategies.

As can be seen from Table 8, as expected, the best results in terms of accuracy were demonstrated by the designed stacking machine learning ensemble for the readiness assessment of R&D products. Therefore it will be used as a base for developing intelligent information technology.

3.2. Assessment Model Development

Figure 5 shows the component diagram. Component "Project" consists of R&D products. The calculation is used for readiness level assessment. Component "User" means the storage of registered users. The component "Result" contains the numerical results of the evaluation. The component "Query" implements the regression coefficients values.

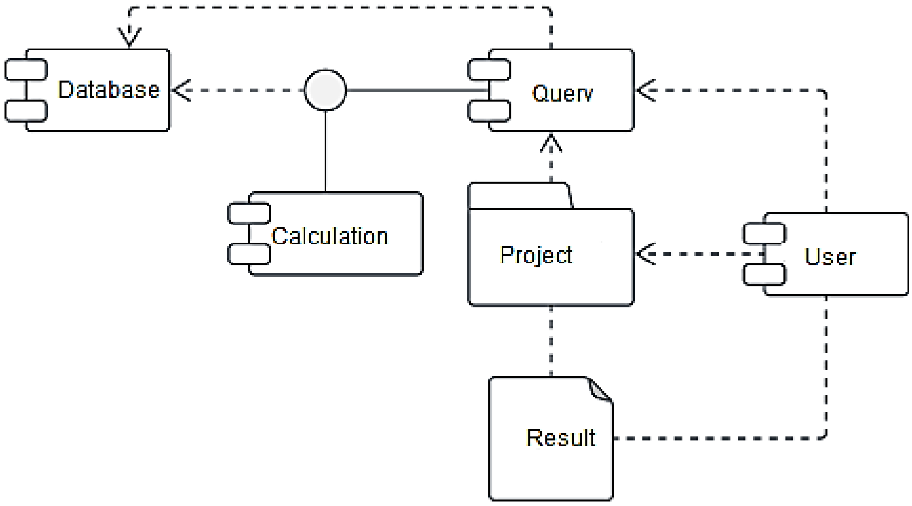


Figure 5. Component diagram.

Figure 6 shows the deployment diagram. The database server is responsible for data saving and management. The workstation is used for system interactions and data visualization. The web server is used for presentation layer realization and as an interface to the database.

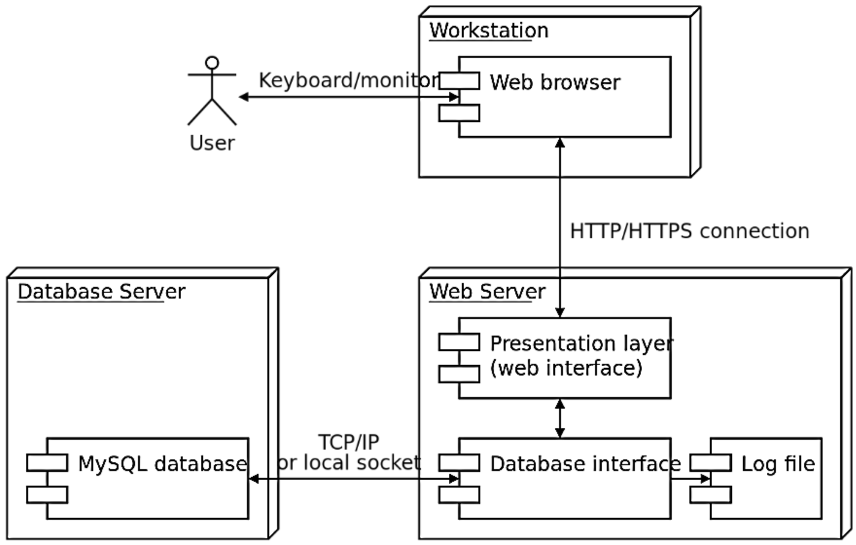


Figure 6. Deployment diagram.

The database schema was developed to assess the readiness level of technologies for the transfer (Figure 7).

Table "Project" is used for project storing. Table "Parameters" consists of parameters for readiness level evaluation. In addition, the estimated coefficient of these parameters is stored. The estimation is built on linear regression.

Table "Project_parameters" is used for expert usage. The categorical variable value helps to estimate the importance of each parameter.

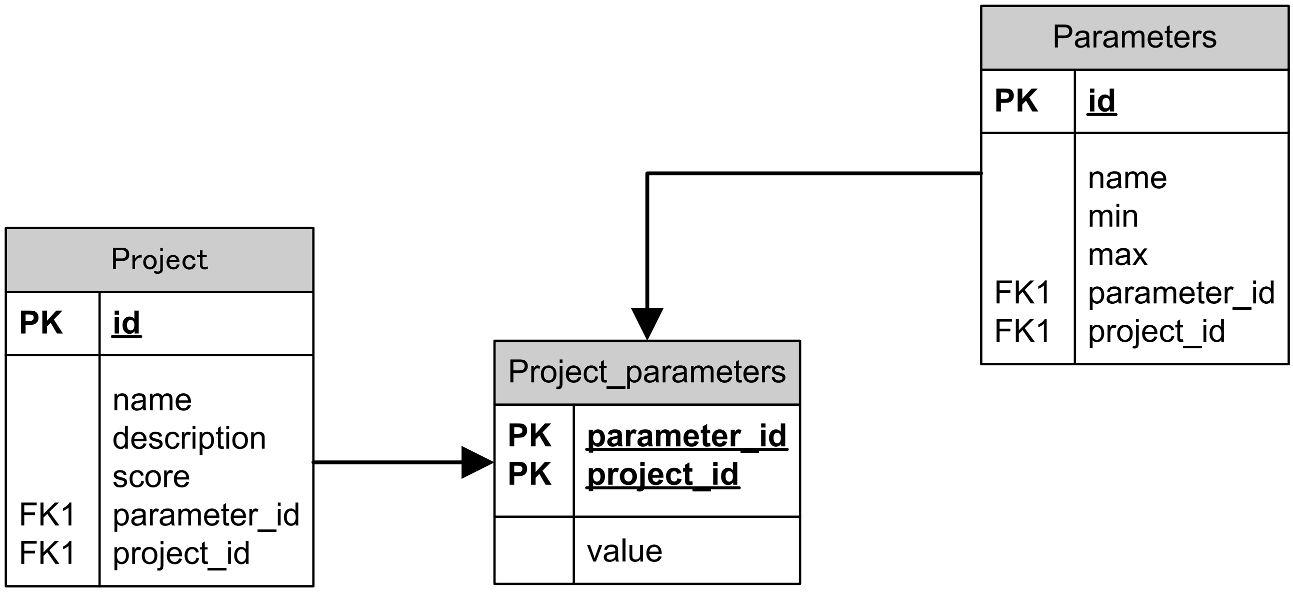


Figure 7. Database schema.

3.3. *System Development and Testing*

The system is implemented as a web-based interface [4].

Figure 8 presents the main webpage of the developed system. The list of R&D products is given in [1,5].

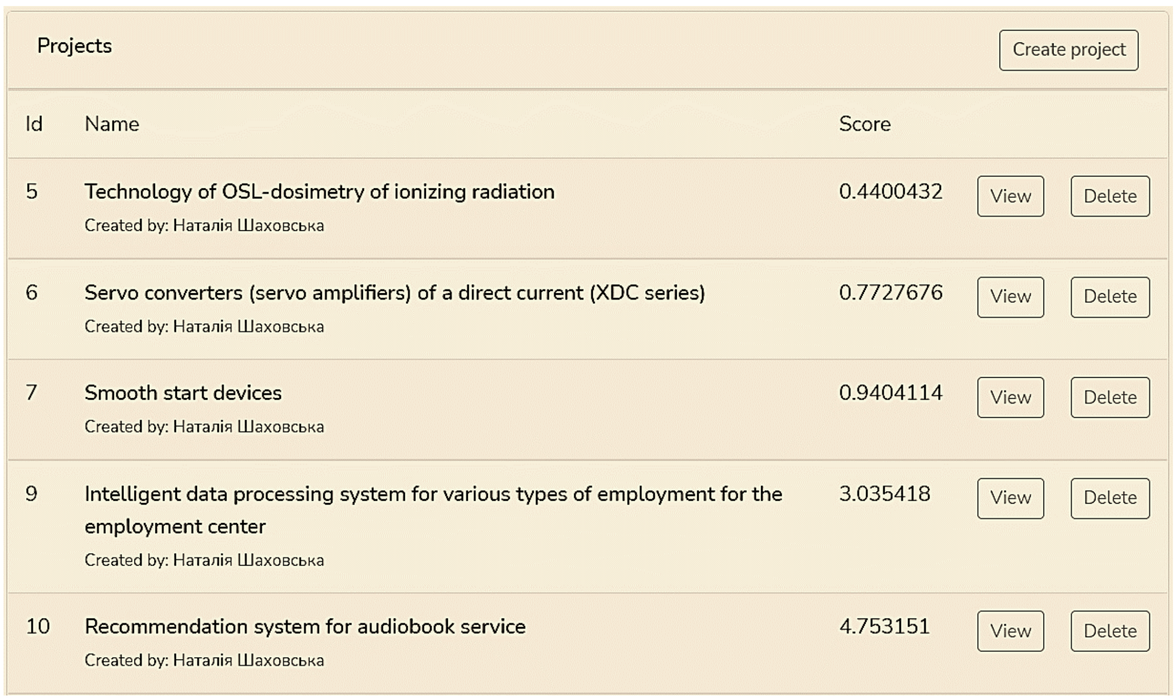


Figure 8. The main page of the information technology.

The system functionality is the following:

- Create project—create new R&D product (Figure 9),
- View project—view the existing R&D product analysis (Figure 10),
- Delete project—delete the current R&D product.

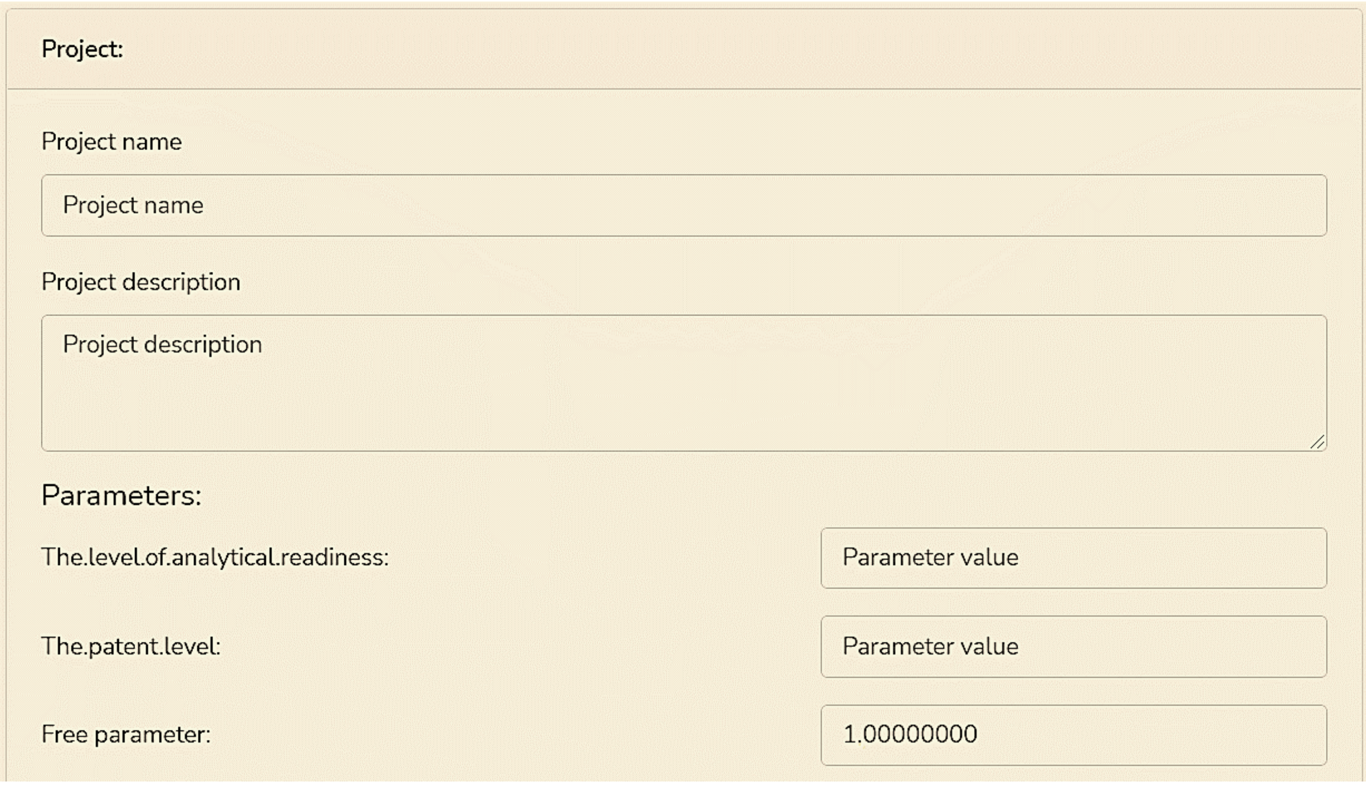


Figure 9. Webpage for new R&D product adding.

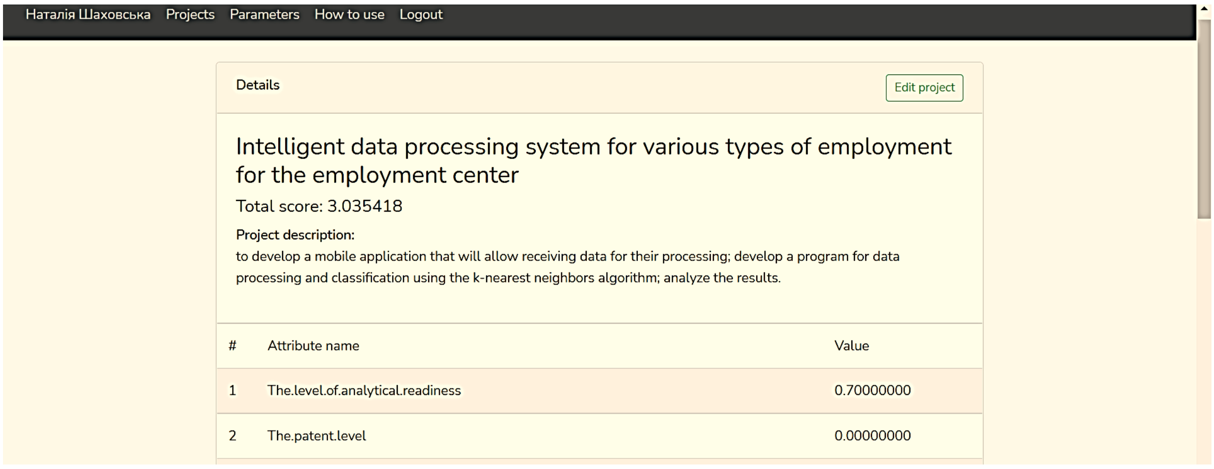


Figure 10. Webpage for product editing.

Next, the model features are given in the system. Figure 11 shows the web page for the parameters' storing and editing. It is possible to add a new parameter or delete an existing parameter. In addition, we can change the coefficient values based on the results of model retraining.

Model retraining is implemented in a different place using RStudio. The model parameters are exported in csv-file and, after that, they are uploaded to the web service.

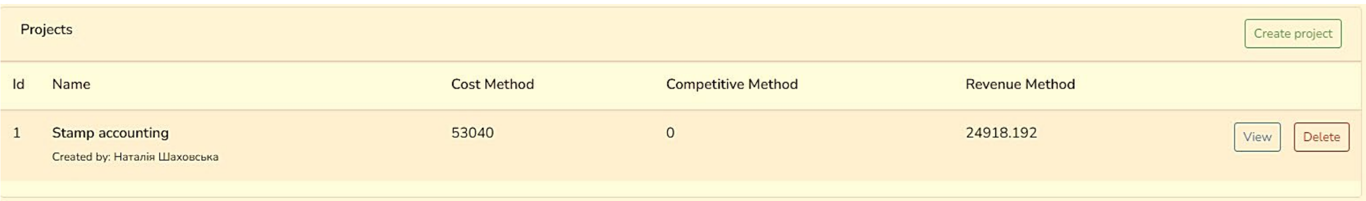
Attributes

Create new

Id	Name	Min	Max	Parameter		
1	The.level.of.analytical.readiness	0.00000000	1.00000000	0.52529000	Edit	Delete
2	The.patent.level	0.00000000	1.00000000	-0.31836000	Edit	Delete
3	Free parameter	1.00000000	1.00000000	3.40463000	Edit	Delete
5	The.demand.readiness.level	0.00000000	1.00000000	-0.44677000	Edit	Delete
6	The.society.impact.level	0.00000000	1.00000000	0.98813000	Edit	Delete
7	Age of the developers	1.00000000	3.00000000	1.20999000	Edit	Delete
8	by the level of depth of change caused by technology	1.00000000	3.00000000	-0.14884000	Edit	Delete
9	by degree of distribution	1.00000000	3.00000000	0.68415000	Edit	Delete
10	depend on technological parameters	1.00000000	3.00000000	-0.17550000	Edit	Delete
11	by areas of development and planning	1.00000000	3.00000000	0.03263000	Edit	Delete
12	by market share coverage	1.00000000	3.00000000	-0.17791000	Edit	Delete
13	the type of the novelty for a market	1.00000000	3.00000000	-0.07564000	Edit	Delete
14	education degree	1.00000000	3.00000000	-1.16970000	Edit	Delete
15	the field of scientific research	1.00000000	3.00000000	0.30483000	Edit	Delete
16	new knowledge mining type	1.00000000	3.00000000	0.26846000	Edit	Delete
17	kind of scientific research	1.00000000	3.00000000	0.34420000	Edit	Delete
18	developers social status	1.00000000	5.00000000	-1.04556000	Edit	Delete
19	the direction of usage for end user	1.00000000	3.00000000	-0.33284000	Edit	Delete
20	the direction of usage	1.00000000	4.00000000	0.02247000	Edit	Delete
21	scope degree	1.00000000	3.00000000	-0.05157000	Edit	Delete
22	innovation potential	1.00000000	3.00000000	0.17842000	Edit	Delete

Figure 11. Web page for model parameters.

The proposed system combines the cost estimating methods of R&D products. Three external users (developer, customer, market expert) have access to the system. The system's main tasks are to calculate the price using various approaches and evaluate the value obtained in general. The system architecture is presented in Figure 12.



Projects

Create project

Id	Name	Cost Method	Competitive Method	Revenue Method		
1	Stamp accounting Created by: Наталія Шаховська	53040	0	24918.192	View	Delete

Figure 12. Web page for R&D product cost estimation.

The proposed approach to assessing the level of readiness of R&D products for commercialization allows:

- determination of an integrated indicator of the readiness level of R&D products for commercialization, calculated based on the indicators' aggregation for each block of the approach. This approach makes it possible to aggregate interdisciplinary positions in evaluating R&D products;
- assessment of the level of readiness of R&D products for a particular evaluation unit; analyzing the possibilities of the commercialization of R&D results in different variations of the ratio of readiness for the components;
- comparison of the levels of readiness of R&D products for commercialization when selecting projects for investment, as the obtained values of the integrated assessments of the readiness levels of R&D products are based on their feasibility study;
- application of the method when deciding whether to include R&D products in the entity's assets.

4. Discussion and Conclusions

This paper presents the model, two methods, and general information technology for:

- R&D products' readiness level assessment;
- R&D products' cost estimation.

The developed R&D products' readiness level assessment model is based on the stacking strategy of the combination of machine learning methods. This is due to the peculiarities of this task. First of all, the readiness of R&D products is assessed by independent experts, many of whom eliminate subjectivism and ensure optimal decision making through majority voting. All this corresponds to Condorcet's jury theorem [36]. To avoid high financial costs for the work of experts, we have proposed a technical solution to this problem, which is to build a stacking ensemble of heterogeneous machine learning methods, the results of which are weighed by the meta-algorithm. In particular, the developed stacking model combines linear regression, *k*-nearest neighbors, support vector machine with radial basis function, and support vector machine with a linear function as the basic machine learning predictors. In addition, the meta-features deformation is added for problems with classical stacking avoidance. The meta-features are the results of weak predictors' training. In the end, deformed features are used together with the training dataset in the meta-model. This combination avoids the correlation of weak predictors' results and increases the model generalization. It allows the RMSE (Root Mean Squared Error) to be decreased a minimum of 1.03 times compared to other ensemble-based approaches.

The paper also presents a complex method for determining the R&D product's cost, which uses the results of the model for the readiness assessment of R&D products, as well as the availability of analogs in the market, and in results provides:

- an increase in the efficiency of transfer, commercialization, and market launch of R&D products,
- promotion of the interaction of all the components of national innovation infrastructure, innovations, etc.

The developed approach can become the main lever for: when deciding on further R&D; the selection and substantiation of investment decisions on the results of R&D, which prepare for commercialization; the development of a pricing strategy, market launch, and further development of R&D products, etc. The proposed methodological support and information system for the transfer and commercialization of R&D products based on their readiness from universities to the external environment will allow:

- to carry out the operational transfer and commercialization of R&D products;
- to develop the policies of market pricing, giving opportunities to clarify the impact of components on the formation of value and, accordingly, the price of R&D products;
- to promptly respond to the market demands for innovation [2];
- to form the basis for the country's successful technological and economic development [3].

From the economic point of view, the application of the proposed methods and models to assess the cost and readiness of the R&D of the product allows specifying such essential elements of the evaluation process as:

- determining the moment and nature of the added value of product R&D (based on the justification of the relationship between levels of readiness and market perception of the product);
- taking into account the dynamism and extractive nature of the R&D product;
- separating the elements in the R&D of the product, which will further contribute to its market convergence, multiplicity, synergy, diffusion, etc. Economic forecasting of the possibility of such effects at the evaluation stage will allow adjusting the price of the product;
- the value expression of tangible and intangible value (object of intellectual property rights) of the R&D product;

- establishing the level of economic feasibility of product transfer/commercialization;
- modeling consumer sensitivity to the purchase of R&D products.

From the standpoint of business practice in commercialization, there are numerous cost evaluation methods [47], but we cannot consider any single technique to be the best one. Each method has its benefits and drawbacks. To reach a better cost and quality estimate, efforts should be made to use a compound of the estimation techniques.

After analysis of the processes of the commercialization of R&D products, it is possible to identify at least four interrelated management pricing decisions, namely:

(a) establishing a system of indicators that affect the price of R&D products;

(b) determining the method of aggregation of unit indicators;

(c) determining the strength of the impact and the importance of indicators (groups of indicators) for participants in the pricing process;

(d) agreeing on the criteria and evaluations of the proposed R&D products between the parties to and setting a final price.

That is why future research will be focused on primary price identification determination. The dataset of the predicted price and real sold price of R&D products should be collected. The collected dataset is too small. That is why a specific method based on a hierarchical predictor is used for small dataset analysis. Five-fold cross-validation is used for results' validation too.

One of the objectives of this study was to develop two software products, the purpose of which is to calculate the level of readiness of the result of R&D products for launch and quickly assess the indicative range of development costs. The use of these software products will be helpful in research incubators, Scientifics Parks, or other structures of the domestic innovation ecosystem. However, this implies the possibility of using the developed software in enterprises or organizations engaged in innovation.

For universities, the application of the author's methods and models to assess the value of R&D products based on their readiness will contribute to:

- striking a balance between "technology push" and "technology pull" strategies for the activities of developers working in university structures;
- the substantiation and selection of potential commercially attractive R&D products at the idea stage;
- a significant reduction in the risk of transferring R&D products from universities to the business environment and their commercialization;
- elaboration of scenarios for the creation of companies such as "spin" (spin-off, spin-out), which are based on the results of the prospects of R&D products, obtained through the author's approach to modeling the value and readiness of products;
- filling gaps in the predominantly low level of entrepreneurial knowledge and competencies of university developers (and, consequently, insufficient level of understanding of market needs and features of commercialization);
- the substantiation of business models of the transfer of R&D products in universities, etc.

In the macroeconomic context, the proposed author's methods and models will increase the level of success of technological entrepreneurship in the country. The obtained methodological and practical results are characterized by duality. On the one hand, the author's developments are valuable for universities when deciding on the transfer of R&D products to the business environment. On the other, they allow modeling of possible factors influencing the product's external environment at the development stage. The proposed methods and models can be used to justify regional development strategies to help bridge the gap between universities and the market.

The limitation of the study is based on the insufficient dataset of R&D products. Due to the analysis of a short dataset, the ensembles were developed. However, the additional proving of the proposed models should be organized based on other datasets' analysis. Future research will also be conducted in the area of applying neural network models [48–50] to build ensemble methods.

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Descriptive Statistics

Table A1. Descriptive statistics for the dataset used for modeling.

	Readiness	The Level of Analytical Readiness	The Patent Level	The Demand Readiness Level	The Society Impact Level	Age	Influence Level	Wide Usage	Technological Complexity	Area	Part of Market	Novelty	Education Level	Scientific Level	New Knowledge	Type of Scientific Research	Social Group
Min.	0.22	0.11	0	0.25	0.25	1	1	1	1	1	1	1	2	2	1	1	4
1st Qu.	0.66	0.44	0	0.5	0.375	3	2	1	1	1	1	2	3	3	2	2	4
Median	0.88	0.56	0	0.5	0.5	3	2	1	2	1	2	3	3	3	2	2	5
Mean	0.78	0.61	0.26	0.58	0.52	2.74	2.37	1.37	1.8	1.81	1.63	2.44	2.81	2.89	1.93	1.96	4.59
3rd Qu.	1	0.775	0.75	0.75	0.75	3	3	2	2.5	2.5	2	3	3	3	2	2	5
Max.	1	1	0.75	1	1	3	3	2	3	5	3	3	3	3	2	2	5

Table A2. Descriptive statistics for the dataset used for modeling.

	Direction of Technology for the Consumer	Direction of Action	Value	Innovative Level
Min.	1	1	1	1
1st Qu.	1	2	1	2
Median	1	2	1	2
Mean	1.96	2.48	1.56	2.41
3rd Qu.	3	3	2	3
Max.	3	4	3	3

Appendix B. Correlation Matrix

Table A3. Correlation matrix.

	Var1	Var2	Freq
1	readiness	readiness	1
2	The.level.of.analytical.readiness	readiness	0.426211
3	The.patent.level	readiness	−0.0648
4	The.demand.readiness.level	readiness	−0.00967
5	The.society.impact.level	readiness	0.21396
6	age	readiness	−0.08677
7	influence.level	readiness	0.133182
8	wide.usage	readiness	0.062229
9	technological.complexity	readiness	−0.18923
10	area	readiness	−0.32458
11	part.of.market	readiness	0.037499
12	novelty	readiness	−0.12008
13	education.level	readiness	−0.04072
14	scientific.level	readiness	0.231502
15	new.knowledge	readiness	0.543526
16	type.of.scientificresearch	readiness	0.284744
17	social.group	readiness	−0.19313
18	direction.of.technology.for.the.consumer	readiness	0.044315
19	direction.of.action	readiness	−0.46876
20	value	readiness	0.040261
21	innovative.level	readiness	−0.1267
22	readiness	The.level.of.analytical.readiness	0.426211
23	The.level.of.analytical.readiness	The.level.of.analytical.readiness	1
24	The.patent.level	The.level.of.analytical.readiness	−0.19353
25	The.demand.readiness.level	The.level.of.analytical.readiness	0.42783
26	The.society.impact.level	The.level.of.analytical.readiness	0.26566
27	age	The.level.of.analytical.readiness	−0.29131
28	influence.level	The.level.of.analytical.readiness	−0.29054
29	wide.usage	The.level.of.analytical.readiness	0.143412
30	technological.complexity	The.level.of.analytical.readiness	0.091115
31	area	The.level.of.analytical.readiness	−0.03075
32	part.of.market	The.level.of.analytical.readiness	0.189293
33	novelty	The.level.of.analytical.readiness	−0.18939
34	education.level	The.level.of.analytical.readiness	−0.3926
35	scientific.level	The.level.of.analytical.readiness	−0.31171
36	new.knowledge	The.level.of.analytical.readiness	0.137015
37	type.of.scientificresearch	The.level.of.analytical.readiness	−0.22991
38	social.group	The.level.of.analytical.readiness	−0.22274
39	direction.of.technology.for.the.consumer	The.level.of.analytical.readiness	0.286185
40	direction.of.action	The.level.of.analytical.readiness	−0.1345
41	value	The.level.of.analytical.readiness	0.262898
42	inovative.level	The.level.of.analytical.readiness	−0.36535
43	readiness	The.patent.level	−0.0648
44	The.level.of.analytical.readiness	The.patent.level	−0.19353
45	The.patent.level	The.patent.level	1
46	The.demand.readiness.level	The.patent.level	−0.35482
47	The.society.impact.level	The.patent.level	−0.35358
48	age	The.patent.level	0.339676
49	influence.level	The.patent.level	0.129253
50	wide.usage	The.patent.level	0.484056
51	technological.complexity	The.patent.level	−0.31177
52	area	The.patent.level	−0.15146
53	part.of.market	The.patent.level	0.166853
54	novelty	The.patent.level	−0.00624
55	education.level	The.patent.level	0.364306
56	scientific.level	The.patent.level	0.270177
57	new.knowledge	The.patent.level	−0.09874
58	type.of.scientificresearch	The.patent.level	0.033424
59	social.group	The.patent.level	0.63362
60	direction.of.technology.for.the.consumer	The.patent.level	−0.69237
61	direction.of.action	The.patent.level	−0.20323
62	value	The.patent.level	0.225471
63	inovative.level	The.patent.level	−0.04959
64	readiness	The.demand.readiness.level	−0.00967
65	The.level.of.analytical.readiness	The.demand.readiness.level	0.42783

Table A3. *Cont.*

	Var1	Var2	Freq
66	The.patent.level	The.demand.readiness.level	−0.35482
67	The.demand.readiness.level	The.demand.readiness.level	1
68	The.society.impact.level	The.demand.readiness.level	0.572469
69	age	The.demand.readiness.level	−0.30198
70	influence.level	The.demand.readiness.level	−0.26485
71	wide.usage	The.demand.readiness.level	−0.02605
72	technological.complexity	The.demand.readiness.level	0.048038
73	area	The.demand.readiness.level	0.045295
74	part.of.market	The.demand.readiness.level	0.242353
75	novelty	The.demand.readiness.level	−0.27552
76	education.level	The.demand.readiness.level	−0.42104
77	scientific.level	The.demand.readiness.level	−0.24019
78	new.knowledge	The.demand.readiness.level	−0.19215
79	type.of.scientificresearch	The.demand.readiness.level	−0.33309
80	social.group	The.demand.readiness.level	−0.33286
81	direction.of.technology.for.the.consumer	The.demand.readiness.level	0.428043
82	direction.of.action	The.demand.readiness.level	0.27417
83	value	The.demand.readiness.level	0.30024
84	inovative.level	The.demand.readiness.level	−0.34266
85	readiness	The.society.impact.level	0.21396
86	The.level.of.analytical.readiness	The.society.impact.level	0.26566
87	The.patent.level	The.society.impact.level	−0.35358
88	The.demand.readiness.level	The.society.impact.level	0.572469
89	The.society.impact.level	The.society.impact.level	1
90	age	The.society.impact.level	−0.11569
91	influence.level	The.society.impact.level	−0.20216
92	wide.usage	The.society.impact.level	−0.06987
93	technological.complexity	The.society.impact.level	−0.21901
94	area	The.society.impact.level	−0.02065
95	part.of.market	The.society.impact.level	0.387471
96	novelty	The.society.impact.level	−0.52462
97	education.level	The.society.impact.level	−0.19109
98	scientific.level	The.society.impact.level	−0.25766
99	new.knowledge	The.society.impact.level	0.199689
100	type.of.scientificresearch	The.society.impact.level	−0.46451
101	social.group	The.society.impact.level	−0.01717
102	direction.of.technology.for.the.consumer	The.society.impact.level	0.276856
103	direction.of.action	The.society.impact.level	0.299626
104	value	The.society.impact.level	0.354286
105	inovative.level	The.society.impact.level	−0.35137
106	readiness	age	−0.08677
107	The.level.of.analytical.readiness	age	−0.29131
108	The.patent.level	age	0.339676
109	The.demand.readiness.level	age	−0.30198
110	The.society.impact.level	age	−0.11569
111	age	age	1
112	influence.level	age	0.266594
113	wide.usage	age	−0.18507
114	technological.complexity	age	0.34125
115	area	age	−0.56224
116	part.of.market	age	0.132431
117	novelty	age	0.28843
118	education.level	age	0.932392
119	scientific.level	age	0.246957
120	new.knowledge	age	0.116743
121	type.of.scientificresearch	age	−0.08717
122	social.group	age	0.406852
123	direction.of.technology.for.the.consumer	age	−0.33419
124	direction.of.action	age	−0.45872
125	value	age	0.089803
126	inovative.level	age	0.290139
127	readiness	influence.level	0.133182
128	The.level.of.analytical.readiness	influence.level	−0.29054
129	The.patent.level	influence.level	0.129253
130	The.demand.readiness.level	influence.level	−0.26485
131	The.society.impact.level	influence.level	−0.20216
132	age	influence.level	0.266594
133	influence.level	influence.level	1

Table A3. *Cont.*

	Var1	Var2	Freq
134	wide.usage	influence.level	−0.2116
135	technological.complexity	influence.level	−0.06786
136	area	influence.level	0.036789
137	part.of.market	influence.level	−0.4707
138	novelty	influence.level	0.48647
139	education.level	influence.level	0.285924
140	scientific.level	influence.level	0.021205
141	new.knowledge	influence.level	−0.05937
142	type.of.scientificresearch	influence.level	0.435204
143	social.group	influence.level	0.131105
144	direction.of.technology.for.the.consumer	influence.level	−0.33787
145	direction.of.action	influence.level	−0.31466
146	value	influence.level	−0.4347
147	inovative.level	influence.level	0.665518
148	readiness	wide.usage	0.062229
149	The.level.of.analytical.readiness	wide.usage	0.143412
150	The.patent.level	wide.usage	0.484056
151	The.demand.readiness.level	wide.usage	−0.02605
152	The.society.impact.level	wide.usage	−0.06987
153	age	wide.usage	−0.18507
154	influence.level	wide.usage	−0.2116
155	wide.usage	wide.usage	1
156	technological.complexity	wide.usage	−0.28201
157	area	wide.usage	0.26795
158	part.of.market	wide.usage	0.307277
159	novelty	wide.usage	−0.3857
160	education.level	wide.usage	−0.02925
161	scientific.level	wide.usage	0.027116
162	new.knowledge	wide.usage	−0.07593
163	type.of.scientificresearch	wide.usage	−0.2557
164	social.group	wide.usage	0.323748
165	direction.of.technology.for.the.consumer	wide.usage	−0.12507
166	direction.of.action	wide.usage	0.34976
167	value	wide.usage	0.420303
168	inovative.level	wide.usage	−0.50062
169	readiness	technological.complexity	−0.18923
170	The.level.of.analytical.readiness	technological.complexity	0.091115
171	The.patent.level	technological.complexity	−0.31177
172	The.demand.readiness.level	technological.complexity	0.048038
173	The.society.impact.level	technological.complexity	−0.21901
174	age	technological.complexity	0.34125
175	influence.level	technological.complexity	−0.06786
176	wide.usage	technological.complexity	−0.28201
177	technological.complexity	technological.complexity	1
178	area	technological.complexity	−0.22252
179	part.of.market	technological.complexity	−0.07762
180	novelty	technological.complexity	0.43589
181	education.level	technological.complexity	0.296648
182	scientific.level	technological.complexity	−0.05
183	new.knowledge	technological.complexity	−0.04
184	type.of.scientificresearch	technological.complexity	−0.02774
185	social.group	technological.complexity	−0.50102
186	direction.of.technology.for.the.consumer	technological.complexity	0.51366
187	direction.of.action	technological.complexity	−0.234
188	value	technological.complexity	−0.1
189	inovative.level	technological.complexity	0.243363
190	readiness	area	−0.32458
191	The.level.of.analytical.readiness	area	−0.03075
192	The.patent.level	area	−0.15146
193	The.demand.readiness.level	area	0.045295
194	The.society.impact.level	area	−0.02065
195	age	area	−0.56224
196	influence.level	area	0.036789
197	wide.usage	area	0.26795
198	technological.complexity	area	−0.22252
199	area	area	1
200	part.of.market	area	−0.15222
201	novelty	area	−0.03028

Table A3. *Cont.*

	Var1	Var2	Freq
202	education.level	area	−0.54416
203	scientific.level	area	−0.64117
204	new.knowledge	area	−0.44505
205	type.of.scientificresearch	area	0.115065
206	social.group	area	−0.00201
207	direction.of.technology.for.the.consumer	area	0.128495
208	direction.of.action	area	0.622087
209	value	area	−0.09429
210	inovative.level	area	0.001583
211	readiness	part.of.market	0.037499
212	The.level.of.analytical.readiness	part.of.market	0.189293
213	The.patent.level	part.of.market	0.166853
214	The.demand.readiness.level	part.of.market	0.242353
215	The.society.impact.level	part.of.market	0.387471
216	age	part.of.market	0.132431
217	influence.level	part.of.market	−0.4707
218	wide.usage	part.of.market	0.307277
219	technological.complexity	part.of.market	−0.07762
220	area	part.of.market	−0.15222
221	part.of.market	part.of.market	1
222	novelty	part.of.market	−0.68554
223	education.level	part.of.market	0.020931
224	scientific.level	part.of.market	−0.0194
225	new.knowledge	part.of.market	0.054331
226	type.of.scientificresearch	part.of.market	−0.39824
227	social.group	part.of.market	0.103422
228	direction.of.technology.for.the.consumer	part.of.market	0.089499
229	direction.of.action	part.of.market	0.16833
230	value	part.of.market	0.747045
231	inovative.level	part.of.market	−0.60899
232	readiness	novelty	−0.12008
233	The.level.of.analytical.readiness	novelty	−0.18939
234	The.patent.level	novelty	−0.00624
235	The.demand.readiness.level	novelty	−0.27552
236	The.society.impact.level	novelty	−0.52462
237	age	novelty	0.28843
238	influence.level	novelty	0.48647
239	wide.usage	novelty	−0.3857
240	technological.complexity	novelty	0.43589
241	area	novelty	−0.03028
242	part.of.market	novelty	−0.68554
243	novelty	novelty	1
244	education.level	novelty	0.309344
245	scientific.level	novelty	0.057354
246	new.knowledge	novelty	−0.22942
247	type.of.scientificresearch	novelty	0.413585
248	social.group	novelty	−0.12228
249	direction.of.technology.for.the.consumer	novelty	−0.08417
250	direction.of.action	novelty	−0.34043
251	value	novelty	−0.65957
252	inovative.level	novelty	0.789338
253	readiness	education.level	−0.04072
254	The.level.of.analytical.readiness	education.level	−0.3926
255	The.patent.level	education.level	0.364306
256	The.demand.readiness.level	education.level	−0.42104
257	The.society.impact.level	education.level	−0.19109
258	age	education.level	0.932392
259	influence.level	education.level	0.285924
260	wide.usage	education.level	−0.02925
261	technological.complexity	education.level	0.296648
262	area	education.level	−0.54416
263	part.of.market	education.level	0.020931
264	novelty	education.level	0.309344
265	education.level	education.level	1
266	scientific.level	education.level	0.43823
267	new.knowledge	education.level	0.229228
268	type.of.scientificresearch	education.level	−0.09349
269	social.group	education.level	0.380911

Table A3. *Cont.*

	Var1	Var2	Freq
270	direction.of.technology.for.the.consumer	education.level	−0.3039
271	direction.of.action	education.level	−0.37324
272	value	education.level	−0.03371
273	inovative.level	education.level	0.311177
274	readiness	scientific.level	0.231502
275	The.level.of.analytical.readiness	scientific.level	−0.31171
276	The.patent.level	scientific.level	0.270177
277	The.demand.readiness.level	scientific.level	−0.24019
278	The.society.impact.level	scientific.level	−0.25766
279	age	scientific.level	0.246957
280	influence.level	scientific.level	0.021205
281	wide.usage	scientific.level	0.027116
282	technological.complexity	scientific.level	−0.05
283	area	scientific.level	−0.64117
284	part.of.market	scientific.level	−0.0194
285	novelty	scientific.level	0.057354
286	education.level	scientific.level	0.43823
287	scientific.level	scientific.level	1
288	new.knowledge	scientific.level	0.35
289	type.of.scientificresearch	scientific.level	−0.06934
290	social.group	scientific.level	−0.0533
291	direction.of.technology.for.the.consumer	scientific.level	−0.13104
292	direction.of.action	scientific.level	−0.32817
293	value	scientific.level	−0.0625
294	inovative.level	scientific.level	0.041959
295	readiness	new.knowledge	0.543526
296	The.level.of.analytical.readiness	new.knowledge	0.137015
297	The.patent.level	new.knowledge	−0.09874
298	The.demand.readiness.level	new.knowledge	−0.19215
299	The.society.impact.level	new.knowledge	0.199689
300	age	new.knowledge	0.116743
301	influence.level	new.knowledge	−0.05937
302	wide.usage	new.knowledge	−0.07593
303	technological.complexity	new.knowledge	−0.04
304	area	new.knowledge	−0.44505
305	part.of.market	new.knowledge	0.054331
306	novelty	new.knowledge	−0.22942
307	education.level	new.knowledge	0.229228
308	scientific.level	new.knowledge	0.35
309	new.knowledge	new.knowledge	1
310	type.of.scientificresearch	new.knowledge	−0.05547
311	social.group	new.knowledge	−0.23452
312	direction.of.technology.for.the.consumer	new.knowledge	0.272554
313	direction.of.action	new.knowledge	−0.468
314	value	new.knowledge	0.025
315	inovative.level	new.knowledge	−0.26854
316	readiness	type.of.scientificresearch	0.284744
317	The.level.of.analytical.readiness	type.of.scientificresearch	−0.22991
318	The.patent.level	type.of.scientificresearch	0.033424
319	The.demand.readiness.level	type.of.scientificresearch	−0.33309
320	The.society.impact.level	type.of.scientificresearch	−0.46451
321	age	type.of.scientificresearch	−0.08717
322	influence.level	type.of.scientificresearch	0.435204
323	wide.usage	type.of.scientificresearch	−0.2557
324	technological.complexity	type.of.scientificresearch	−0.02774
325	area	type.of.scientificresearch	0.115065
326	part.of.market	type.of.scientificresearch	−0.39824
327	novelty	type.of.scientificresearch	0.413585
328	education.level	type.of.scientificresearch	−0.09349
329	scientific.level	type.of.scientificresearch	−0.06934
330	new.knowledge	type.of.scientificresearch	−0.05547
331	type.of.scientificresearch	type.of.scientificresearch	1
332	social.group	type.of.scientificresearch	−0.16261
333	direction.of.technology.for.the.consumer	type.of.scientificresearch	−0.20352
334	direction.of.action	type.of.scientificresearch	−0.3245
335	value	type.of.scientificresearch	−0.45069
336	inovative.level	type.of.scientificresearch	0.442219
337	readiness	social.group	−0.19313

Table A3. *Cont.*

	Var1	Var2	Freq
338	The.level.of.analytical.readiness	social.group	−0.22274
339	The.patent.level	social.group	0.63362
340	The.demand.readiness.level	social.group	−0.33286
341	The.society.impact.level	social.group	−0.01717
342	age	social.group	0.406852
343	influence.level	social.group	0.131105
344	wide.usage	social.group	0.323748
345	technological.complexity	social.group	−0.50102
346	area	social.group	−0.00201
347	part.of.market	social.group	0.103422
348	novelty	social.group	−0.12228
349	education.level	social.group	0.380911
350	scientific.level	social.group	−0.0533
351	new.knowledge	social.group	−0.23452
352	type.of.scientificresearch	social.group	−0.16261
353	social.group	social.group	1
354	direction.of.technology.for.the.consumer	social.group	−0.86046
355	direction.of.action	social.group	0.10647
356	value	social.group	0.13325
357	inovative.level	social.group	0.058147
358	readiness	direction.of.technology.for.the.consumer	0.044315
359	The.level.of.analytical.readiness	direction.of.technology.for.the.consumer	0.286185
360	The.patent.level	direction.of.technology.for.the.consumer	−0.69237
361	The.demand.readiness.level	direction.of.technology.for.the.consumer	0.428043
362	The.society.impact.level	direction.of.technology.for.the.consumer	0.276856
363	age	direction.of.technology.for.the.consumer	−0.33419
364	influence.level	direction.of.technology.for.the.consumer	−0.33787
365	wide.usage	direction.of.technology.for.the.consumer	−0.12507
366	technological.complexity	direction.of.technology.for.the.consumer	0.51366
367	area	direction.of.technology.for.the.consumer	0.128495
368	part.of.market	direction.of.technology.for.the.consumer	0.089499
369	novelty	direction.of.technology.for.the.consumer	−0.08417
370	education.level	direction.of.technology.for.the.consumer	−0.3039
371	scientific.level	direction.of.technology.for.the.consumer	−0.13104
372	new.knowledge	direction.of.technology.for.the.consumer	0.272554
373	type.of.scientificresearch	direction.of.technology.for.the.consumer	−0.20352
374	social.group	direction.of.technology.for.the.consumer	−0.86046
375	direction.of.technology.for.the.consumer	direction.of.technology.for.the.consumer	1
376	direction.of.action	direction.of.technology.for.the.consumer	0.140598
377	value	direction.of.technology.for.the.consumer	0.091725
378	inovative.level	direction.of.technology.for.the.consumer	−0.27271
379	readiness	direction.of.action	−0.46876
380	The.level.of.analytical.readiness	direction.of.action	−0.1345
381	The.patent.level	direction.of.action	−0.20323
382	The.demand.readiness.level	direction.of.action	0.27417
383	The.society.impact.level	direction.of.action	0.299626
384	age	direction.of.action	−0.45872
385	influence.level	direction.of.action	−0.31466
386	wide.usage	direction.of.action	0.34976
387	technological.complexity	direction.of.action	−0.234
388	area	direction.of.action	0.622087
389	part.of.market	direction.of.action	0.16833
390	novelty	direction.of.action	−0.34043
391	education.level	direction.of.action	−0.37324
392	scientific.level	direction.of.action	−0.32817
393	new.knowledge	direction.of.action	−0.468
394	type.of.scientificresearch	direction.of.action	−0.3245
395	social.group	direction.of.action	0.10647
396	direction.of.technology.for.the.consumer	direction.of.action	0.140598
397	direction.of.action	direction.of.action	1
398	value	direction.of.action	0.114146
399	inovative.level	direction.of.action	−0.21313
400	readiness	value	0.040261
401	The.level.of.analytical.readiness	value	0.262898
402	The.patent.level	value	0.225471
403	The.demand.readiness.level	value	0.30024
404	The.society.impact.level	value	0.354286
405	age	value	0.089803

Table A3. *Cont.*

	Var1	Var2	Freq
406	influence.level	value	−0.4347
407	wide.usage	value	0.420303
408	technological.complexity	value	−0.1
409	area	value	−0.09429
410	part.of.market	value	0.747045
411	novelty	value	−0.65957
412	education.level	value	−0.03371
413	scientific.level	value	−0.0625
414	new.knowledge	value	0.025
415	type.of.scientificresearch	value	−0.45069
416	social.group	value	0.13325
417	direction.of.technology.for.the.consumer	value	0.091725
418	direction.of.action	value	0.114146
419	value	value	1
420	inovative.level	value	−0.76575
421	readiness	inovative.level	−0.1267
422	The.level.of.analytical.readiness	inovative.level	−0.36535
423	The.patent.level	inovative.level	−0.04959
424	The.demand.readiness.level	inovative.level	−0.34266
425	The.society.impact.level	inovative.level	−0.35137
426	age	inovative.level	0.290139
427	influence.level	inovative.level	0.665518
428	wide.usage	inovative.level	−0.50062
429	technological.complexity	inovative.level	0.243363
430	area	inovative.level	0.001583
431	part.of.market	inovative.level	−0.60899
432	novelty	inovative.level	0.789338
433	education.level	inovative.level	0.311177
434	scientific.level	inovative.level	0.041959
435	new.knowledge	inovative.level	−0.26854
436	type.of.scientificresearch	inovative.level	0.442219
437	social.group	inovative.level	0.058147
438	direction.of.technology.for.the.consumer	inovative.level	−0.27271
439	direction.of.action	inovative.level	−0.21313
440	value	inovative.level	−0.76575
441	innovative.level	inovative.level	1

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