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# DEVISING A METHODOLOGICAL APPROACH TO IDENTIFYING THE ECONOMIC POTENTIAL OF PRODUCTION COSTS FOR ECO-INNOVATIVE PRODUCTS

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***The object of this study is the production costs of ecologically oriented innovative products.***

***The problem under consideration was to improve the efficiency of cost management for the production of eco-innovative products by improving the methodical approach to identifying reserves for their reduction in order to ensure competitive advantages and strengthen the economic and environmental security of the enterprise.***

***The devised methodological approach is based on a systematic analysis using economic and mathematical methods. It provides for the establishment of the dependence of costs per dollar of eco-innovative products on factors related to the economic potential of the enterprise, and the search for reserves for reducing costs for the production of eco-innovative products.***

***The analysis technology was substantiated and modeling of costs per dollar of eco-innovative products of the enterprise was carried out using the principal component analysis. A distinctive feature of the built model was the consideration of the influence of micro-level factors, risk management, and the innovative component of the enterprise's economic potential. The resulting model is significant and reliable since the variation of costs per dollar of innovative products depends on the change in the principal components under investigation by 85 %.***

***Within the framework of the devised methodical approach, a technology for calculating reserves for reducing production costs of enterprises producing eco-innovative products has been proposed. It was established that the potential of reducing costs per dollar of eco-innovative products for the totality of the investigated enterprises is on average 5.4 cents per dollar of costs.***

***The area of practical use of the devised methodical approach is the process of minimizing and optimizing costs per hryvnia of eco-innovative products***

***Keywords: eco-innovations, environmental safety, cost management, component modeling, cost reduction reserves***

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## 1. Introduction

The latest challenges and the aggravation of globalization confrontations have slowed down the economic rhythm and brought the national economy to a crisis. Today's realities require the introduction of advanced technologies and innovations that can provide for the implementation of the Recovery Plan for Ukraine, presented in July 2022 in Lugano (Switzerland) [1]. The prerequisite for its implementation and the only sure way out of the ecological and economic crisis is the development and implementation of innovations with a high degree of environmental friendliness and economic efficiency. The driver of the transition to innovative low-waste, waste-free, and environmentally friendly production technologies is ecological innovation. It is they who provide enterprises with competitive advantages, help to win, and keep part of the market, increase profitability in these markets, provide for the productivity and independence of both enterprises and the state as a whole.

Actualization of the growth of social, public, ecological, and economic effect from the introduction of ecological innovations activates the search for the newest and modernization of existing approaches, methods and tools for managing costs for the production of eco-innovative products. Analytical support for management decision-making is gaining more and more importance in this context. In order to make informed decisions about the costs of production of eco-innovative products, the analysis should be comprehensive and provide comprehensive, up-to-date information about their composition, structure and level, implementation of the cost optimization mechanism. The practical implementation of the problem of improving analytical support and increasing the informativeness of management of production costs necessitates the development of a methodological toolkit for assessing their effectiveness based on economic and mathematical methods. Modeling costs for the production of eco-innovative products will allow enterprises to effectively determine the direction of costs, identify the best ways to reduce and optimize them, and form appropriate management strategies. The results of such studies are also relevant in the context of increasing the level of environmental safety of business entities and creating an environment for the development of their innovative potential.

## 2. Literature review and problem statement

Under the conditions of global challenges, the strengthening of eco-innovation trends and the increasing interest of consumers in choosing environmentally friendly products fundamentally change the traditional ideas about the main factors influencing the commercial success of business entities. In work [2], the authors, based on network and symbiotic structures for industrial eco-innovations, reviewed the literature on eco-innovations with the participation of manufacturing companies and provided a comprehensive understanding of their essence. But the issues related to defining the scope of the problem and the requirements for implementing eco-innovations for the economic growth of business entities remained unresolved. The search for an answer to these questions is described in work [3], which contains the results of a broad patent analysis, based on which a number of problems and requirements for eco-innovations are highlighted, which are divided into 14 general eco-categories. The authors define primary eco-engineering contradictions, if eco-problems appear as negative side effects of new technologies, and secondary eco-engineering contradictions, if environmentally friendly solutions have new ecological disadvantages. At the same time, there are no proposals in the work for leveling the identified contradictions and eliminating shortcomings to increase the environmental safety of enterprises due to the intensification of production processes. An option to overcome the relevant difficulties may be the implementation of new approaches to the management of the production of innovative products. This is the approach used in paper [4], which reports a study of the effectiveness of the organization of clean production and innovativeness of industry, a complex network of sustainable industrial practices, with an emphasis on the impact of the methodology on the environment and resource efficiency. But the question remains unsolved, which is connected with the search for reserves to reduce innovation costs, which would contribute to the long-term improvement of production. A relevant solution under these conditions is the implementation of management practices proposed in [5], which are understood as strategic actions of generating and introducing innovations into production, based on the idea of reverse material flows. However, these practices do not take into account the issue of cost management, which involves the development and implementation of managerial influences based on economic laws to shape and regulate costs in accordance with strategic and current goals. Study [6] considers the creation of a management strategic model of eco-innovations, adapted to the method of classical SWOT analysis, as a tool for obtaining information about the eco-innovation process in order to standardize the collection of evidence. At the same time, the work lacks a comprehensive perception of the problem, which leaves unresolved the issue of harmonizing the functions and tasks of the management system of innovative production costs with the general enterprise management system. An option to overcome the relevant difficulties may include a system of finding ways to gradually reduce costs and achieve the target cost and profitability of production, proposed in work [7]. Analysis of variance and analysis of cost drivers are also effective tools, which are used to determine the change in the cost price due to the influence of factors developed in works [8, 9]. To determine the risk of key cost drivers, it is advisable to use such a tool as the Ishikawa diagram and simulations, which are substantiated in work [10]. But the issues related to the multi-level impact on innovation costs of each of the economic factors during modeling remained unresolved. The reason for this may be objective difficulties associated with the fact that analytical calculations carried out by traditional methods of elimination cannot determine and measure their diversity. An option to overcome the relevant difficulties is to include in the production cost analysis model the factors that directly shape them (costs of materials, wages, etc.) and those that act indirectly. The latter include labor productivity, capital return, turnover of current assets, and others. This is the approach used in work [11], which uses detailed multifactorial regression analysis to establish the legitimacy of the selection of factors in the practice of economic analysis. However, with a large number of signs, the characterization of the identified relationships becomes time-consuming. There is a need to group information, that is, to describe objects with a smaller number of generalizing indicators, in particular factors or principal components. Therefore, it is advisable to use component modeling to identify reserves for reducing and increasing the efficiency of costs for the production of eco-innovative products of the enterprise.

The results of a critical analysis of the literature [2–11] show that currently there are no developments to solve the problem of ensuring competitive advantages, increasing the efficiency of cost management, and strengthening the economic and environmental safety of the enterprise through effective analytical methods. All this gives reason to assert that it is expedient to conduct a study aimed at devising a methodical approach for identifying the cost-effectiveness potential for the production of eco-innovative products using the tools of economic and mathematical modeling.

## 3. The aim and objectives of the study

The purpose of our study is to devise a methodical approach to identifying the cost-effectiveness potential for the production of eco-innovative products. This will make it possible to determine the reserves of cost reduction and compile recommendations for their optimization, which in a single system will increase the efficiency of cost management, provide competitive advantages, and strengthen the economic and environmental safety of the enterprise.

To achieve the goal, the following tasks were set:

– to build an economic-mathematical model of the dependence of costs in the production of eco-innovative products;

– to work out a technology for identifying reserves for reducing costs in the production of eco-innovative products.

## 4. The study materials and methods

The object of our study is the enterprise's costs for the production of eco-innovative products, which are understood as products made from polymer materials taking into account the factors of minimizing the negative impact on the environment. The production process of eco-innovative products includes the use of environmentally friendly materials, energy-efficient technologies, and reduction of waste and pollution.

The main hypothesis of the research assumes that there is an opportunity to identify the cost-effectiveness potential for the production of eco-innovative products through the development of an appropriate methodical approach that allows the enterprise to provide competitive advantages, economic stability, and environmental safety.

Assumptions adopted in the study:

– costs for the production of eco-innovative products can be represented in the form of an economic-mathematical model.

– there are reserves for reducing costs for the production of eco-innovative products, which can be identified and used for their optimization;

– the economic aspect of cost management has a direct impact on the competitiveness of the enterprise, its economic and environmental safety.

Simplifications of the current research:

– it is assumed that all costs for the production of eco-innovative products can be adequately represented by an economic-mathematical model;

– possible indirect effects of other factors on costs, except those directly related to the production process, are not taken into account.

The research was carried out using the principal component analysis, which implies determining combinations of linear random variables based on the characteristics of vectors in the covariance matrix. The principal components are an orthogonal coordinate system, in which the variances of the components characterize their statistical properties and are more convenient aggregate indicators. They reflect internal objectively existing regularities that can be directly observed [12, 13].

On the basis of the obtained correlation matrix during the correlation-regression analysis, regression equations are built that connect the factor characteristics with the resulting indicator. The regression equations are the final format for the implementation of the research tasks and are used for meaningful economic interpretation of results. When applying the principal component analysis, the correlation matrix is considered as the initial stage for further analysis of the previously obtained values of features [14, 15]. Therefore, it is possible to obtain additional information about the researched object or process.

In view of the above, the analysis of production costs at enterprises producing eco-innovative products was carried out in accordance with the devised technology (Fig. 1).

The first stage of the technology of cost analysis for the production of eco-innovative products involves the implementation of four tasks aimed at assessing the closeness of the relationship between the studied indicators. First, a meaningful and strictly justified selection of indicators is carried out to assess the cost-effectiveness in accordance with the set goal. Next, the matrix normalization of the initial data is carried out to eliminate heterogeneity in the measurement of the initial indicators. After that, a correlation matrix is built and based on it, the nature of the close relationship between the selected indicators is evaluated.


Fig. 1. Technology for analyzing eco-innovation costs of the enterprise by the principal component analysis (developed by Authors)

The second stage of the technological algorithm for the analysis of costs for the production of eco-innovative products includes the sequential implementation of five tasks focused on the interpretation of the statistical characteristics of the factor matrix. The first step is to obtain the primary factor matrix. Next – recognition of the economic nature of the revealed regularities, finding the most characteristic properties of the studied economic phenomena. Then – determining the reliability of statistical factor loadings; determination of the dispersion of the selected indicators in the dispersion of the initial indicators, meaningful interpretation from the point of view of economic theory. Finally, the interpretation and comparative analysis of the factor matrix.

The third stage of the analysis of the eco-innovative production technology involves the construction of the principal components based on the selected factor matrix. At this stage, the principal components are quantified by weighting the values of the initial indicators using a factor matrix.

The fourth stage of the technology of component analysis consists in the direct construction of regression equations on the principal components. In the process of analyzing regression equations, the influence of complex factors (components) on the formation of initial indicators is also investigated.

The cost indicator for one dollar of eco-innovative products was used as a modeled indicator. The component analysis was carried out on the basis of data for three years (2021–2023), which are contained in the forms of accounting and statistical reporting of 25 enterprises in the cities of Ukraine, the main activity of which is the production of innovative ecological polymer products. These enterprises have different organizational and legal forms, sizes, stages of the life cycle, located in different cities, but their aggregate is characterized by similar operating conditions and micro- and meso-level factors that affect production efficiency, and is formed taking into account the requirements for the volume and homogeneity of the sample population, which provides for its representativeness.

## 5. Results of devising a methodical approach to identifying the cost-effectiveness potential for the production of eco-innovative products

### 5. 1. An economic-mathematical model of the dependence of costs on the production of eco-innovative products

In the course of the study, a system of indicators was formed that characterizes the efficiency of the use of labor resources (return on capital ($X_1$), the specific weight of the active part of fixed assets ($X_3$). Also, objects of work (material intensity ($X_7$) and labor force (number of production personnel ($X_6$), turnover of circulating means ($X_2$), average wage ($X_5$), wage intensity ($X_8$), and labor productivity of one production worker ($X_4$). When building a system of indicators, the need to include features characterizing the specific weight of general production costs ($X_9$) was taken into account. Along with efficiency, the selected indicators characterize the quality of work and management of the production of eco-innovative products. The collected initial information was checked for accuracy, homogeneity, and compliance with the law of normal distribution, according to the effective and factor indicators (Table 1).

Listed in Table 1, the results show that the variability of the variation series does not exceed 33 %, which allows us to draw a conclusion about the homogeneity of the studied population. The calculation of asymmetry and kurtosis indicators showed that the studied information is subject to the law of normal distribution since the asymmetry and kurtosis error indicator is less than 3. Thus, the selected population can be recognized as meeting the conditions of representativeness, which fully and adequately represents the properties of the general population. In order to determine the closeness of the relationship of the analyzed indicators, a correlation matrix was calculated on their basis (Table 2).

The analysis of correlation coefficients showed that the selected indicators are in a fairly close relationship. Based on the qualitative assessment of the closeness of the connection according to Chaddock, it can be concluded that there is a close relationship between the costs per dollar of innovative products and the return on capital ($X_1$) ($r$=0.871). There is a significant relationship ($r$=0.564) between costs per dollar of innovative products and the specific weight of general production costs ($X_9$).

There is a moderate relationship between costs per dollar of innovative products and other indicators. Checking the correlation coefficients according to the Student's test showed that the value of the correlation coefficients is significant. At a 5 % confidence level, the calculated value of $t$ is higher than the tabular value ($t$=2.021). Since $t$ is actual for $X_1$ – 2.059, $X_2$ – 2.8869, $X_3$ – 5.5539, $X_4$ – 3.5689, $X_5$ – 3.2743, $X_6$ – 5.3443, $X_7$ – 5.6906, $X_8$ – 2,8724, $X_9$ – 7.1045.

Table 1

Indicators of the statistical characteristics of the initial information of the sample population of enterprises for 2021–2023 (calculated by Authors)

| Indicator | Legend | Arithmetic mean | RMS deviation | Variance, % | Error | |
|---|---|---|---|---|---|---|
| | | | | | Asymmetry | Kurtosis |
| Costs per $1 of eco-innovative products, USD | $Y$ | 0.754 | 0.068 | 9.085 | 0.283 | 0.566 |
| Return on capital, USD | $X_1$ | 17.231 | 2.900 | 16.833 | 0.283 | 0.566 |
| Turnover of working capital, days | $X_2$ | 32.240 | 6.187 | 19.189 | 0.283 | 0.566 |
| Share of the active part of fixed assets, % | $X_3$ | 61.275 | 6.497 | 10.603 | 0.283 | 0.566 |
| Average annual labor productivity of one production worker, USD/person | $X_4$ | 15,333.491 | 2,982.263 | 19.449 | 0.283 | 0.566 |
| Average annual salary per production worker, USD/person | $X_5$ | 5,261.669 | 1,468.436 | 27.908 | 0.283 | 0.566 |
| Share of production workers in the total number of personnel of the enterprise, % | $X_6$ | 67.453 | 9.893 | 14.666 | 0.283 | 0.566 |
| Material consumption, USD | $X_7$ | 0.281 | 0.065 | 23.309 | 0.283 | 0.566 |
| Salary intensity USD | $X_8$ | 0.343 | 0.084 | 24.528 | 0.283 | 0.566 |
| Share of general production costs in the output of innovative products, % | $X_9$ | 17.916 | 2.909 | 16.237 | 0.283 | 0.566 |

Table 2

Correlation matrix

| – | $Y$ | $X_1$ | $X_2$ | $X_3$ | $X_4$ | $X_5$ | $X_6$ | $X_7$ | $X_8$ | $X_9$ |
|---|---|---|---|---|---|---|---|---|---|---|
| $Y$ | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $X_1$ | 0.871 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $X_2$ | 0.304 | 0.09 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| $X_3$ | 0.49 | 0.539 | 0.112 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| $X_4$ | 0.361 | 0.347 | –0.04 | 0.115 | 1 | 0 | 0 | 0 | 0 | 0 |
| $X_5$ | 0.337 | 0.255 | 0.119 | 0.099 | 0.586 | 1 | 0 | 0 | 0 | 0 |
| $X_6$ | 0.479 | 0.38 | 0.192 | 0.324 | –0.02 | 0.047 | 1 | 0 | 0 | 0 |
| $X_7$ | 0.498 | 0.432 | –0 | 0.26 | 0.281 | –0.07 | 0.179 | 1 | 0 | 0 |
| $X_8$ | 0.303 | 0.22 | 0.061 | 0.087 | 0.026 | 0.222 | 0.288 | –0.05 | 1 | 0 |
| $X_9$ | 0.564 | 0.438 | 0.462 | 0.345 | 0.035 | 0.2 | 0.234 | 0.03 | 0.123 | 1 |

The processing of raw data by the principal component analysis involves the transition from indicators of the economic activity of the studied objects according to 9 indicators (X) to generalizing indicators (principal components). The principal component method is based on a linear model. If $N$ is the number of objects under investigation, $n$ is the number of features (measured characteristics of the object), then the mathematical model of the transition from indicators ($x$) to the principal components ($f$) takes the form (1):

$$x'_j = \sum\nolimits_{r=1}^{n} a_{jr} f_r, \qquad (1)$$

where $r, j$=1, 2, ..., $n$; $f_r$ – $r$-th principal component; $a_{jr}$ is the weight of the $r$th component of the $j$th variable; $x'_j$ – the centered (normalized) value of the $j$th feature obtained in the model; $x_j$ is the normalized value of the $j$th feature obtained from the experiment, based on observations.

The number of principal components $r=n$ here corresponds to the number of features $n$. Therefore, in the full model of the principal components, the entire variance of the investigated process is exhausted. Formula (2) should be used to find the transition operator matrix from signs to principal components:

$$A = U\Lambda^{1/2}, \qquad (2)$$

where $U$ is the matrix of eigenvectors, $\Lambda$ is the diagonal matrix of eigenvalues.

Finding the principal components of the population is reduced to the determination of eigenvalues – $\lambda_r$ and eigenvectors – $U_r$ for the matrix of covariances of the random vector $X$. At the same time, the eigenvalues ($\lambda_r$) are the variance of the principal components ($f_r$). To determine the eigenvalues (values), the obtained correlation matrix (Table 2) was used, and a characteristic equation was built, which takes the following form:

$$|R-\lambda E| = \begin{vmatrix} 1-\lambda & 0.0903 & 0.5393 & 0.347 & 0.2551 & 0.3804 & 0.4321 & 0.2204 & 0.4379 \\ 0,0903 & 1-\lambda & 0.1123 & -0.039 & 0.1187 & 0.1923 & 0 & 0.0608 & 0.4619 \\ 0,5393 & 0.1123 & 1-\lambda & 0.115 & 0.099 & 0.3236 & 0.2605 & 0.0866 & 0.3452 \\ 0.3474 & -0.039 & 0.1155 & 1-\lambda & 0.5865 & -0.0235 & 0.2809 & 0.0264 & 0.0351 \\ 0.2551 & 0.1187 & 0.099 & 0.586 & 1-\lambda & 0.0474 & -0.068 & 0.2217 & 0.2004 \\ 0.3804 & 0.1923 & 0.3236 & -0.024 & 0.0474 & 1-\lambda & 0.1789 & 0.2884 & 0.234 \\ 0.4321 & 0 & 0.2605 & 0.281 & -0.068 & 0.1789 & 1-\lambda & -0.051 & 0.0305 \\ 0.2204 & 0.06080 & 0.0866 & 0.026 & 0.2217 & 0.2884 & -0.051 & 1-\lambda & 0.1227 \\ 0.4379 & 0.4619 & 0.3452 & 0.035 & 0.2004 & 0.234 & 0.0305 & 0.1227 & 1-\lambda \end{vmatrix} = 0.$$

In order for this characteristic equation to have a non-zero solution, it is necessary and sufficient that its determinant is equal to zero. The determinant of the matrix ($R$–$\lambda E$) is a polynomial of power $m$ with respect to $\lambda$ (3):

$$|R-\lambda E| = (-1)^m \lambda^m + (-1)^{m-1} p_1 \lambda^{m-1} + \ldots + p_m, \qquad (3)$$

where $p_1 = trR = (r_{11} + r_{22} + \ldots + r_{mm})$, $p_m = |R|$.

This polynomial is the characteristic polynomial of the correlation matrix $R$. To solve this equation, formulas (4) should be used:

$$\begin{array}{lll} R_1 = R; & p_1 = tr(R_1); & B_1 = R_1 - p_1 E; \\ R_2 = RB_1; & p_2 = \frac{1}{2} tr(R_2); & B_2 = R_2 - p_2 E; \\ \ldots & \ldots & \ldots \\ R_{m-1} = RB_{m-2}; & p_{m-1} = \frac{1}{m-1} tr(R_{m-1}); & B_{m-1} = R_{m-1} - p_{m-1} E; \\ R_m = RB_{m-1}; & p_m = \frac{1}{m} tr(R_m); & B_m = R_m - p_m E. \end{array} \qquad (4)$$

The roots of the characteristic polynomial $|R-\lambda E|$ are the characteristic numbers or eigenvalues of the matrix $R$. As a result of solving the characteristic equation, the following eigenvalues are acquired, which can be represented in matrix form:

$$\lambda = \begin{vmatrix} 2.692 & 0 & 0 & 0 & 0 \\ 0 & 1.503 & 0 & 0 & 0 \\ 0 & 0 & 1.331 & 0 & 0 \\ 0 & 0 & 0 & 1.073 & 0 \\ 0 & 0 & 0 & 0 & 0.742 \end{vmatrix}.$$

In this matrix, the eigenvalues determine the contribution of the corresponding principal component to the total variance.

Total variance:

$$V = \sum_{r=1}^{n} V = tr(R) = \\ = n = 9.$$

The contributions to the total variance of each principal component and the total contribution of the first components are given in Table 3.

Table 3 demonstrates that the share of variance explained by the extracted first five principal components is 81.59 % of the total variance of the studied process. The further process of calculating the principal components was stopped due to a sharp drop in the value of the contribution of the principal components to the total variance. The total contribution of other components is about 18 %. Thus, the first five extracted principal components were used for further analysis.

Table 3

The total contribution of the removed components according to the data of a sample population of enterprises for 2021–2023 (calculated by authors)

| Criterion | Principal component | | | | |
|---|---|---|---|---|---|
| | *F*1 | *F*2 | *F*3 | *F*4 | *F*5 |
| Contribution components | 2.692 | 1.503 | 1.332 | 1.074 | 0.742 |
| Contribution of components in percentage | 29.91 | 16.7 | 14.8 | 11.93 | 8.246 |
| The total contribution of the first components | 29.91 | 46.61 | 61.41 | 73.35 | 81.59 |

**5. 2. Technology for identifying reserves for reducing costs in the production of eco-innovative products**

The forecasting of costs for the production of eco-innovative products is carried out taking into account the fact that each eigenvalue corresponds to its own vector of the matrix *R*. The eigenvalues of the material symmetric matrix are material, and the eigenvectors corresponding to different eigenvalues of the material symmetric matrix are orthogonal. Therefore, finding the eigenvectors for the selected components is performed by solving a system of linear equations:

$$\begin{aligned}&(r_{11}-\lambda)x_1+r_{12}x_2+\ldots+r_{1m}x_m=0;\\&r_{21}x_1+(r_{22}-\lambda)x_2+\ldots+r_{2m}x_m=0;\\&\ldots\\&r_{m1}x_1+r_{m2}x_2+\ldots+(r_{mm}-\lambda)x_m=0,\end{aligned}$$

where $r_{ij}$ is the corresponding element of the correlation matrix; λ is an eigenvalue for which an eigenvector is determined; $x_{1\ldots m}$ are the sought elements of the eigenvector.

As a result, the matrix of the obtained eigenvectors for the extracted five principal components takes the following form:

$$U=\begin{Vmatrix}0.509 & 0.058 & -0.209 & -0.035 & -0.151\\0.217 & -0.377 & 0.365 & 0.428 & 0.487\\0.406 & -0.131 & -0.261 & 0.042 & -0.563\\0.276 & 0.64 & 0.086 & 0.126 & 0.146\\0.283 & 0.45 & 0.496 & -0.006 & -0.059\\0.338 & -0.307 & -0.103 & -0.387 & 0.272\\0.263 & 0.158 & -0.585 & 0.126 & 0.511\\0.213 & -0.079 & 0.292 & -0.722 & 0.137\\0.38 & -0.314 & 0.251 & 0.334 & -0.209\end{Vmatrix}.$$

Using formula (2), the weighting coefficients – operators of the transition from indicators (*X*) to the principal components (*F*) are determined (Table 4).

On the basis of the matrix of weighting coefficients, the relationship of the indicators selected for interpretation with the selected principal components is determined. As is obvious from Table 3, the first principal component explains 29.91 % of the total variance of the process.

Table 4

Weighting coefficients based on the data of a sample population of enterprises that manufactured eco-innovative products in 2021–2023 (calculated by Authors)

| Indicator | Principal component | | | | |
|---|---|---|---|---|---|
| | $F_1$ | $F_2$ | $F_3$ | $F_4$ | $F_5$ |
| $X_1$ | 0.835521 | −0.266493 | 0.468052 | 0.585512 | 0.243854 |
| $X_2$ | −0.0952 | −0.46239 | −0.15122 | −0.66357 | 0.387996 |
| $X_3$ | 0.343229 | −0.4479 | 0.301508 | 0.89118 | 0.427392 |
| $X_4$ | 0.74764 | 0.525042 | 0.04817 | −0.13032 | 0.051033 |
| $X_5$ | 0.05803 | 0.597674 | 0.249808 | 0.150935 | −0.70054 |
| $X_6$ | −0.30358 | 0.02401 | 0.155097 | 0.110887 | −0.78324 |
| $X_7$ | −0.47948 | −0.71201 | 0.212091 | 0.017723 | −0.03707 |
| $X_8$ | −0.50277 | −0.81731 | 0.128315 | −0.34675 | −0.39442 |
| $X_9$ | −0.81566 | −0.14699 | 0.16419 | −0.60941 | −0.39542 |

A group of closely related indicators included in this component is formed by indicators (Table 4): return on capital ($X_1$) (0.835521), average annual productivity of one production worker ($X_4$) (0.74764), specific weight of ZVV ($X_9$) (−0.81566). At the same time, if the first two indicators have positive values of coefficients, then the indicator of the share of ZVV has a negative value. This indicates that the effect of the specified feature is opposite to the results of the first two. In other words, with an increase in the rate of return on capital and the average annual productivity of production workers, the specific weight of ZVV decreases. The set of these indicators reflects the organizational and technical level of production. In this regard, it is advisable to define the first principal component as "Organizational and technical level of innovative production".

The second principal component explains 16.7 % of the total variance of the process (Table 3). In this principal component, the indicators of material intensity ($X_7$) and salary intensity ($X_8$) turned out to be the most important (weight coefficients −0.71201 and −0.81731). The negative relationship of these indicators with the second principal component is fully justified since the reduction of these indicators helps to increase the efficiency of production activities. Based on this, the second principal component can be defined as a factor characterizing the level of resource use.

The set of indicators that determines the economic content of the third principal component (which explains 14.8 % of the total variance of the process) forms a factor that characterizes the use of fixed assets. This includes indicators of return on capital ($X_1$) (weight factor 0.468052) and shares of the active part of fixed production assets ($X_3$) (0.301508). The analyzed interrelationship of these indicators allows us to define this component as "the level of use of fixed assets".

The fourth principal component explains 11.93 % of the total variance of the process (Table 3). This component with high weighting factors includes indicators of return on capital ($X_1$) and turnover of working capital ($X_2$) (weighting factors of 0.585512 and 0.89118, respectively). They reflect the degree of use of fixed and working capital, as well as the indicator of the specific weight of ZVV (−0.60941). The common feature of these indicators is that their calculation is based on the volume of produced eco-innovative products.

The combination of these indicators characterizes the level of management of innovative production.

The economic content of the fifth principal component can be explained with the help of indicators: the average annual salary of one production worker ($X_5$) (–0.70054) and the average registered number of production personnel ($X_6$) (weight factor –0.78324). It is most expedient to define the fifth component as the level of use of labor resources.

The orthogonality of the principal components makes it possible to construct a regression equation based on them, in which the coefficient estimates are independent of each other. This favorably distinguishes it from the regression equation built on the original data, correlated with each other, independent variables. With the help of regression analysis, it is possible to determine the influence of the principal components on economic indicators.

The model obtained using the principal component analysis takes the following form (5):

$$y = a_0 + a_1 f_1 + a_2 f_2 + \ldots + a_n f_n, \quad (5)$$

where $y$ is the modeled indicator, $a_n$ is the weighting factor for the $n$-th principal component, $f_n$ is the $n$th principal component.

Thus, if earlier the change in costs per dollar of innovative products of each enterprise was influenced by 9 features, now this influence can be concluded based on five new, but generalized characteristics – the principal components. The extracted five principal components were used as generalizing factors to approximate economic indicators using a linear regression model.

Based on the matrix of principal components, calculated by multiplying the matrices of variables and weighting factors, the following regression equation (6) was constructed:

$$y = 0.754 - 0.013 f_1 + 0.022 f_2 - \\ -0.026 f_3 - 0.032 f_4 - 0.005 f_5, \quad (6)$$

where $y$ – costs per dollar of eco-innovative products, $f_1$ – "Organizational and technical level of innovative production", $f_2$– "Level of use of resources", $f_3$ – "Level of use of fixed assets", $f_4$– "Level of management of innovative production", $f_5$ – "The level of use of labor resources."

In order to verify the accuracy of the obtained regression equation and the legality of its use for practical purposes, the reliability of the relationship indicators was assessed. For this, Fisher's test ($F$-ratio), average error of approximation, coefficient of multiple correlation ($R$) and determination ($D$) were defined. The actual value of the $F$-ratio is 79.994, which is higher than its tabular value, therefore, the hypothesis that there is no relationship between the costs per dollar of innovative products and the studied components is rejected. The smaller the theoretical regression line (calculated by the equation) deviates from the actual (empirical), the smaller the average approximation error. Taking into account that an error of 5–8 % is allowed in economic calculations, it can be concluded that the studied relationship equation determines the studied dependences quite accurately since its average error of approximation is 0.02738 or 2.74 %.

The completeness of the connection can be judged by the value of multiple coefficients of correlation ($R$) and determination ($D$). According to the derived equation, $R$=0.923, $D$=0.852. This means that 85 % of the variation in costs per dollar of innovative products depends on the change in the principal components being studied, while other factors account for 15 % of the variation in the performance indicator. Therefore, it can be concluded that the resulting model of the principal components is significant and reliable, it can be used for practical purposes: assessment of the results of enterprise activity, calculation of reserves for reducing costs for the production of eco-innovative products, planning and forecasting.

The constructed regression equation makes it possible to determine how, on average, over the analyzed years, production costs at enterprises decreased, and under the influence of which principal components this happened. The advantage of the regression equation built on the principal components over the usual equation, in which the initial indicators act as factor characteristics, is that the free term of the equation characterizes the average values of costs per dollar of eco-innovative products (in the study, it is equal to 0.754). This allows one to determine the value of the modeled indicator in its pure form, that is, only due to the selected principal components.

According to the proposed model of cost reduction per dollar of eco-innovative products, for the totality of enterprises and the studied years, the average was 5.4 cents per dollar of costs (–1.3+2.2–2.6–3.2–0, 5). This happened mainly under the influence of a group of factors characterizing "Level of innovative production management" ($F_4$) and "Level of use of fixed assets" ($F_3$). The inconsistency of the organizational and technical level with the needs of innovative production ($F_1$) and insufficiently efficient use of labor resources ($F_5$) causes an increase in costs and contains reserves for their reduction.

The conclusions drawn are reliable since the selected components determine 81.59 % of the variance in the initial indicators (Table 3). In addition, the share of the influence of the selected components on the change in costs per dollar of innovative products for 2021–2023 was 79.994 % (value $F$ – relationship), which indicates its determining nature.

Calculation of beta coefficients (standardized regression coefficients) allows us not only to compare all the principal components but also to measure them quantitatively when the performance indicator changes by one standard deviation. This is done by multiplying the coefficients for the principal components by the ratio of the root mean square deviation for each root mean square deviation variable for the performance indicator. Thus, when the indicator of costs per dollar of innovative products deviates, the first principal component will decrease by:

0.089((–0.013)×(0.467/0.068)).

The second will increase by:

0.340(0.022×(1.066/0.068)),

the third, fourth and fifth components will decrease respectively by:

0.331((–0.026)×(0.879/0.068)),

0.638((–0.032)×(1.355/0.068)),

0.076((–0.005)×(1.018/0.068)).

The comparison of beta coefficients made it possible to study the degree of influence of each principal component on the value of the performance indicator. It was found that the level of management of innovative production (–0.638) and the level of use of fixed assets (–0.331) have the greatest impact on costs per dollar of innovative products in the studied enterprises.

The final stage of component modeling is the solution of the inverse factor problem, which consists in estimating with the help of weight coefficients the contribution of each performance indicator ($X$) to the change in costs per dollar of innovative products of the analyzed enterprises.

The feedback analysis of the principal components with the selected indicators is a further development of the component analysis. With the help of such a solution of the factor problem, internal reserves for reducing the cost of innovative products are determined. The purpose of the inverse factor problem is to identify indicators from among those selected for analysis that affect the weighting factors that can affect the change of the principal components. The solution to the direct factor problem involves the analysis of regression equations that characterize the influence of the selected principal components on the selected initial indicators [16, 17].

It is expedient to analyze the equations for qualitative indicators, expanding the equality of the $i$-th characteristic (7):

$$x_i = a_{i1_1} F_1 + a_{i2} F_2 + .....a_{in} F_n, \qquad (7)$$

where $X_i$ is the normalized value of the $i$th feature, $F_{1,2...n}$ is the $n$th principal component, $a_{i1,\,2..n}$ is the weight of the $n$th component in the $i$th variable.

The obtained regression equations for the studied quality indicators and their statistical estimates are given in Table 5. The given data prove the reliability of regression equations and the possibility of their use in the process of making effective management decisions [18].

Table 5

Reverse factor analysis of the studied quality indicators by the totality of enterprises (2021–2023) (calculated by Authors)

| Indicator | Regression equation | $R$ | $R^2$ | $F$-ratio |
|---|---|---|---|---|
| Return on capital, USD | $X$=17.231+0.836$F_1$––0.266$F_2$+0.468$F_3$++0.585$F_4$+0.244$F_5$ | 0.858 | 0.759 | 81.34 |
| Turnover of circulating assets, days | $X$=32–0.095$F_1$––0.462$F_2$–0.151$F_3$–0.664$F_4$+0.388$F_5$ | 0.930 | 0.796 | 79.91 |
| Average annual labor productivity of one production worker, USD | $X$=15333.49+0.748$F_1$++0.525$F_2$+0.048$F_3$––0.13$F_4$+0.05$F_5$ | 0.872 | 0.849 | 77.52 |
| Material consumption, USD | $X$=0.281–0.479$F_1$––0.712$F_2$+0.212$F_3$++0.018$F_4$–0.037$F_5$ | 0.943 | 0.881 | 78.02 |
| Salary intensity, USD | $X$=0.343–0.503$F_1$––0.817$F_2$+0.128$F_3$––0.347$F_4$–0.394$F_5$ | 0.923 | 0.862 | 79.41 |

According to the resulting coefficients of the equations reflecting the quantitative influence of each component, the growth of capital return occurs mainly under the influence of the first principal component, which characterizes the organizational and technical level of innovative production ($F_1$) (the coefficient is 0.836). Its positive impact is weakened by insufficient use of available resources ($F_2$) (the coefficient is –0.266). The influence of other principal components, regarding the use of fixed assets, labor, and the efficiency of management of innovative production, is also aimed at increasing the return on capital. At the same time, reserves for increasing the rate of return on capital at enterprises that manufacture innovative products are related to the improvement of the use of production resources and the improvement of the organizational and technical level of innovative production since these factors have the greatest influence on it.

The first four components, whose coefficients are $F_1$ – (–0.095), $F_2$ – (–0.462), $F_3$ – (–0.151), $F_4$ – (–0.664), have a negative impact on the indicator of turnover of current assets. As a result, the turnover increase reserve mainly depends on increasing the level of management of innovative production. That is, due to the increase of variability coefficients, the use of machines and equipment by capacity, rationalization of the selection of their types, rationing, control of general production costs, that is, the $F_3$ component, the influence of which is the strongest.

It is the organizational and technical level of innovative production that has a positive effect on the indicator of the average annual productivity of one production worker (the coefficient is 0.748). However, its influence is weakened by insufficiently efficient management of innovative production (the coefficient is 0.13). Based on the coefficients of the equation, the reserve for increasing labor productivity is an increase in the level of use of fixed assets ($F_3$) and labor resources ($F_5$), due to an increase in the level of mechanization and automation of work, the use of new progressive technologies and innovations.

The change in the indicator of material intensity and wage intensity depends on the second principal component ($F_2$), with the coefficients of the equation (–0.712) and (–0.817), respectively. This component, which characterizes the level of use of production resources, contains the main characteristics of their efficiency, and also has a high impact on the studied indicators.

## 6. Discussion of results of the identified cost-effectiveness potential for the production of eco-innovative products

Component modeling was carried out on the basis of data characterizing the efficiency, quality of work, and management of production activities for 2021–2023 in a sample of 25 Ukrainian industrial enterprises, the main activity of which is the production of innovative environmentally safe polymer products. The original information was checked for accuracy, homogeneity, and compliance with the law of normal distribution (Table 1). The close relationship between costs per dollar of innovative products and micro-level factors determining its changes was determined (Table 2). Taking into account the content of micro-level factors, the principal components affecting the change in the cost price of one dollar of eco-innovative products were determined (Table 4). A multifactor regression equation (6) was also built to determine how the average cost of production of eco-innovative products changed over the analyzed years and under the influence of which principal components this happened [19–21].

In the course of our study, the level of utilization of the available capacities of enterprises producing eco-innovative products was determined, and the technology for determining reserves for reducing costs for its production was devised. To calculate the forecast values of the key parameters of the studied enterprises, a regression model was used, which includes indicators of the structure and efficiency of the use of the economic potential of the enterprise. Namely: structure of fixed assets and capital return; personnel structure, average annual labor productivity and salary of one production worker; share of total production costs of production of eco-innovative products, material intensity, salary intensity and turnover of working capital. The obtained point forecast values were used to determine reserves for reducing costs per dollar of innovative products [22, 23]. The model built proves that the studied enterprises have significant reserves of reducing costs for the production of eco-innovative products, which are contained in five principal components. At the same time, it is the use of the principal component analysis that contributes to the timely and objective identification of potential opportunities for increasing the efficiency of costs for the production of innovative products [24, 25].

The results of the reverse factor analysis of quality indicators given in Table 5 confirm the effectiveness of the proposed model of forecasting the level of innovation costs based on the matrix of the principal components (6). This demonstrates the versatility and effectiveness of the designed analytical apparatus for developing cost management strategies and increasing the efficiency of production of eco-innovative products [26, 27].

At the same time, this study has certain shortcomings and limitations related to the limits of application of the results and the stability of decisions to changing factors. Among the shortcomings of the study, it is possible to single out the lack of an established information and analytical service, which will allow optimizing the process of determining reserves for reducing costs for the production of eco-innovative products through the use of modern digital solutions [28–30]. Regarding restrictions. Our results and recommendations are correct in the context of the production of eco-innovative polymer products and may be inadequate for other industries. The universality of the results is limited by the time period of the study (2021–2023), and they may be sensitive to changes in the business environment or internal factors of enterprises, which may lead to the need for periodic updating.

In general, the results obtained in the course of the study will contribute to solving the problems of increasing the efficiency of management of eco-innovation costs. It is promising to combine the capabilities of axonometric and prognostic models. As well as methods of mathematical and statistical extrapolation to determine the main trends of changes in the cost of eco-innovative products, modeling, forecasting and decision-making to increase the economic efficiency of costs for the production of eco-innovative products.

## 7. Conclusions

1. In order to optimize costs for the production of ecologically oriented innovative products, a methodical approach to identifying their cost-effectiveness potential, based on economic and mathematical modeling, has been devised. Using the principal component analysis, an economic-mathematical model of the level of costs for the production of eco-innovative products was built. The structure of this model is a linear equation that reflects the dependence of costs per dollar of eco-innovative products on factors related to the availability and efficiency of the use of production resources and costs of the enterprise, the quality of work and production management. According to the resulting model, the greatest decrease in costs per dollar of innovative products (0.032) is determined due to the improvement of the level of management of innovative production per unit. Its size is somewhat smaller (0.026; 0.013; 0.005) – due to the increase by one unit of the organizational and technical level of innovative production and the levels of use of fixed assets and labor resources, respectively.

2. The model built is recommended to be used for calculating reserves of cost reduction for the production of eco-innovative products, planning and forecasting. The technology for identifying potential opportunities to reduce the level of costs in the production of ecologically oriented innovative products involves calculating the difference between current and optimal costs and identifying factors that have the greatest potential for reducing costs per dollar of eco-innovative products. It provides an opportunity to optimize the main indicators of activity, contributes to increasing their economic and environmental safety. The revealed possibilities of reducing costs per dollar of eco-innovative products are a guarantee of increasing the competitiveness of enterprises on the basis of sustainable development and taking into account the European green course.

## Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

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## Data availability

All data are available in the main text of the manuscript.

## Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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