WSB Journal of Business and Finance
Year 0000, Vol. 56, No.1
eISSN 2657-4950

Decision-Making Of Innovation Pattern During Development Of Innovation Strategy Of Industrial Enterprise In Conditions Of Uncertainty And Risk

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DOI 10.2478/WSBJBF-2022-0005

Abstract

Developing a suitable innovation strategy is crucial for the success of the enterprise and to increase its competitiveness. However, uncertainty and risk should be taken into account when the innovation strategy is developed. The aim of this work offering practical recommendations for the selection of innovation patterns for developing innovation strategy of an enterprise in conditions of uncertainty and risk by using retrospective analysis of innovation activity. *Research objectives*: Analysis of the concept of pattern-making of innovations and classification of innovations by patterns; development of method of quantitative measurement of innovation patterns and determination of intervals of values of the indicator of innovativeness, corresponding to each pattern; development of methodology and justification for the algorithm for decision-making on the innovation pattern during the development of innovation strategy on the basis of determination of degree of influence of each pattern on the economic indicators of the enterprise. *Results of the work*: The methodology of decision-making on the selection of innovation pattern, based on a combination of two decision-making methods: grey relational analysis and TODIM with determination of evaluating criteria weights using method IDOCRIW, is developed. *Conclusions*: The proposed methodology creates the opportunity to select innovation pattern with the least risk during development of innovation strategy of an enterprise because of the combination of calculation of closeness of each alternative to ideal alternative with pairwise comparison of alternatives taking into account expected losses, related to selection of each alternative. The paper proposes a method for choosing an innovation pattern based on a combination of two decision-making methods, largely presented in the works indexed in Scopus and Web of Science: grey relational analysis and the TODIM method. The presented methods of decision-making are based on the determination of the weights of the evaluation criteria, characterizing the significance of each of them. The weights of the criteria are proposed to be calculated using the IDOCRIW method. This method performs an objective determination of the weights of criteria based on determining the degree of dominance of the values of each criterion with simultaneous assessments of losses for each criterion. The proposed methodology allows for a detailed analysis of innovation patterns acting as evaluated alternatives, taking into account all criteria used in the evaluation and also the losses associated with the choice of each alternative.

Keywords: innovation strategy of the enterprise, innovation pattern, fuzzy set theory, retrospective analysis of innovation activity, regression analysis, method IDOCRIW, grey relational analysis, method TODIM

1 Introduction

The concept of creating patterns of innovations based on their classification was proposed by Japanese scientists U. Atsuda et al. (Atsuda et al., 2008). The patterning of innovations refers to the classification of innovations according to various patterns. These researchers identify four patterns of innovation: pattern 1, pattern 2, pattern 3, and pattern 4. Pattern 1 is characterized by the development of fundamentally new technologies and their introduction into production with a focus on new productions, new products, a new market, and the creation of new advantages radically

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different from the advantages associated with large-scale and established customer potential. Innovations related to this pattern create a new market that is radically different from the existing market. Pattern 2 represents innovations aimed at creating a new market based on the use of existing technologies that are reusable and modernized, the so-called core technologies. Pattern 3 consists of the development and application of fundamentally new technologies in order to radically improve the quality of existing products. Pattern 4 consists of improving the quality of existing products based on the application and gradual modernization of core technologies with the sale of the products in the existing market.

Each of the innovation patterns has its own level of innovation. Pattern 1 is characterized by the highest level of innovation, since innovations related to the development and implementation of fundamentally new technologies and the manufacture of new products based on them focus on new production methods and form a new market radically different from the existing market. Pattern 2 also has a high level of innovation, but this level is lower compared to pattern 1 due to targeting the target audience in the existing market, which, as a rule, prefers familiar products. Pattern 3 is characterized by a lower level of innovation compared to the previous two innovation patterns, since it uses core technologies that do not undergo significant changes when they are introduced into the manufacturing process of the final product. Pattern 4 corresponds to the lowest level of innovation, since this pattern assumes consistent innovative development with gradual improvement of core technologies and products manufactured using them, sold in an existing stable market with a target audience that prefers familiar products. Given the presented classification according to the level of novelty, innovation patterns can be grouped. Two patterns, patterns 1 and 3, refer to basic innovations, while the other two patterns, patterns 2 and 4, refer to enhancement innovations. For the convenience of differentiating innovation patterns and analysing them in order to select the most preferred pattern in the development of an innovative strategy for an industrial enterprise, the authors propose to divide them in such a way that the numbers of patterns belonging to the same type, in accordance with the classification of innovations by the level of novelty, are grouped together: pattern 1 – the development of fundamentally new technologies, the release of radically new products and the creation of a new market with their help; pattern 2 – development and application of fundamentally new technologies in order to create a fundamentally new product or to radically improve the quality of manufactured products, with the implementation of the final product in the existing market and focus on its target audience; pattern 3 – creation of a new market or entry into a new market based on the use of existing core technologies (Core Technologies); pattern 4 – improving the quality of manufactured products based on the application and gradual modernization of existing basic technologies with the sale of manufactured products in the existing market.

Atsuda et al. (2008) noted the high importance of innovation patterning for the effectiveness of an enterprise's innovative activity. The authors of this paper argue that an enterprise needs to optimize the innovation process as part of the implementation of innovation activities in order to create the possibility of effectively converting technologies that are important in the creation and implementation of innovations into an innovative product, while emphasizing that the nature of the innovation process determines the impact of innovation on consumers. In this context, the patterning of innovations can become a guide to the rational implementation of innovation activities, expressed in minimizing unnecessary, unreasonable and uneven costs, which will create the possibility of maximizing the efficient use of resources, primarily technologies, and, in addition, will allow targeted strategic management of the impact of innovations on consumers. At the same time, the positive impact of the patterning of innovations on the effective use of not only technologies but also other resources is noted. The number of resources used in the innovation process, in addition to technologies related to information resources, also includes human resources (human resources), material resources (machinery and equipment) and financial resources. With regard to financial resources, Atsuda et al. consider risk capital as an important category. The patterning of innovations can reduce the likelihood of various risks and the amount of risk capital as a measure of accidental loss (value-at-risk, VAR) associated with risks related to innovation activities due to a significant contribution to the growth of the efficiency of the enterprise while ensuring the use value and value of the enterprise. From the standpoint of human resources at work (Atsuda et al., 2008), attention is focused on the need to develop an entrepreneurial spirit among staff, especially among technical specialists directly involved in the innovation process. The patterning of innovations will allow employees with an entrepreneurial spirit to involve the majority of personnel in innovative activities with the help of tacit knowledge, which will increase the efficiency of the enterprise by enhancing communication between employees. The immediate effect of the patterning of innovations is to increase the efficiency of the innovation process, including both the actual creation of an innovative product and the impact of the results of innovation on consumers.

From this, we can conclude that the choice of the optimal pattern of innovation is an essential factor in improving the efficiency of the innovation activity of an industrial enterprise, considering various aspects. For the successful implementation of innovative products on the market, an enterprise needs to create products that are most in demand among consumers, which largely depends on the degree of their novelty, characterized by the level of innovation, since consumers may have different attitudes towards product novelty. In some situations, consumers are conservative and prefer only familiar products. With such conservatism, demand for innovative products is possible, but the consumer will give preference to familiar products with some new properties. It is also possible that a consumer may be ready to purchase a significantly updated product that can create a new market but at the same time has some of the properties familiar to the consumer and remains within the framework of the usual product, which can be created by upgrading core technologies. At the same time, even if the consumer is ready to purchase a fundamentally new product,

he may seek to satisfy old needs with it and, in this case, the consumer purchases the products that fulfil the needs of the target audience in the existing market. The development and application of fundamentally new technologies with the subsequent creation of a radically new product and a new market, which corresponds to pattern 1, contains both high risks and significant opportunities for an industrial enterprise, since such products may be negatively perceived by consumers when entering the market and, accordingly, may not have significant demand. The product may also have a significant demand due to the intensive development of a new market created with the help of these products and the attractiveness for consumers of products that have radically new properties that are better than the properties of products available on the existing market. As a result, we can conclude that the choice of the innovation pattern, from the standpoint of consumers' perceptions of the degree of novelty of the produced innovative products, can be considered as a factor that has a significant impact on its use value, which is the ability of the product to satisfy certain consumer needs. At the same time, the enterprise must also take into account the cost of producing products corresponding to each innovation pattern. A high level of production costs, even if these costs are paid off when the product is sold on the market, can become a source of risk in the long run. At the same time, different patterns of innovation, differing in the degree of novelty, may require different costs for producing the products. In some cases, innovation patterns that are more novel may require higher production costs, but the development and implementation of new technologies can also improve the efficiency of production processes and the management of resources used within them, thereby reducing the costs associated with their production.

Thus, the choice of the optimal pattern of innovations should be aimed at finding the optimal variant that ensures maximum demand for innovative products produced by an industrial enterprise at the lowest possible cost of production. Identification of an innovation pattern that meets these conditions can optimize the risks associated with a lack of demand for innovative products manufactured by an industrial enterprise on the market, as well as the risks associated with excessive production costs, significantly increasing the efficiency of innovation and contributing to high profitability, economic growth and financial stability of an industrial enterprise. In addition to the actual increase in the economic efficiency of innovation and the economic growth of the enterprise, this will also have additional advantages in terms of creating favourable conditions for attracting investment for the innovation activity. With regard to human resources, the optimization of risks associated with the implementation of innovative products on the market and excessive costs for their production can be considered as a significant factor in reducing the risk of resistance to innovation on the part of personnel and will make it possible to maximize the use of human resources in line with ensuring and increasing the efficiency of the enterprise's innovative activities. This determines the relevance and importance of developing a methodology for choosing the optimal pattern of innovations as part of the formation of an innovative strategy for an industrial enterprise, which allows maximizing the demand for manufactured innovative products and minimizing the costs associated with their production. Since innovation is associated with uncertainty and risk and decisions regarding innovation are made under these conditions, the methodology must take into account both the advantages of each pattern and the costs associated with its choice.

The optimal innovation pattern for an industrial enterprise should be determined on the basis of a retrospective analysis of its innovation activity. The optimality criterion is the maximization of demand for innovative products while minimizing the cost of their production. The main form of innovation activity is the implementation of innovative projects. An innovative project is an organizational and technological scheme of work on the creation, implementation, development and distribution of new types of products or processes. At the same time, innovative projects represent the organizational framework for the implementation of the innovation process at an enterprise or a group of enterprises – systematic and based on methodological rules for obtaining knowledge, ideas and results. A retrospective analysis of innovation activity is an analysis of earlier implemented innovative projects with the establishment of a pattern of innovations created and implemented within each of them, followed by an assessment of the degree of influence of each innovation pattern on the indicators characterizing the economic growth of the industrial enterprise.

2 Literature review

The basis for determining the pattern of innovations created within each individual innovation project is a quantitative assessment of their level of innovativeness. The authors propose using the concepts of G.M. Mutanov, Z.S. Esengalieva (Mutanov, Esengalieva, 2012) and fuzzy set theory to conduct such an assignment. G.M. Mutanov and Z.S. Esengalieva consider innovative projects as objects of two interacting segments: science and business, and propose to consider them as two-dimensional objects: innovativeness (I) and competitiveness (K). They propose to calculate the values of these criteria using a method based on determining the average values of expert assessments for each criterion of innovativeness and competitiveness. They refer to the criteria of innovativeness as compliance of the project with the priority directions of the industrial and innovative strategy, the relevance of the research and the uniqueness of the project, the scientific novelty of the solutions proposed in the project, the technological level of the project (new technology), the advantages of the project compared to existing analogues in the world and the economic feasibility of the project. The general indicator of innovativeness G.M. Mutanov and Z.S. Esengalieva propose to define as (Mutanov, Esengalieva, 2012) (1):

$$I_j = \sum_{i=1}^{n} x_i f_{ij,} \sum_{i=1}^{n} x_i = 1 \qquad (1)$$

where f_{ij} is the value of the i-criterion of the j-th project for the indicator of innovation; x_i is the value of the weight coefficient of the i, the criterion for the indicator of innovation; n is the number of criteria for the indicator of innovativeness, $n = 6$. The range of values of the general indicator of innovativeness is from 1 to 9.

The authors used the fuzzy set approachto select membership functions to determine the membership degree of each specific innovation project to a specific innovation pattern. For this purpose, the membership function $\mu(A)x$ ("high innovativeness"), characterized by a monotonous increase and the allocation on it of intervals of values corresponding to one or more membership degree characteristics to the fuzzy set "high innovativeness", which corresponds to a specific innovation pattern, is necessary. The authors believe that four approximately equal intervals should be distinguished that correspond to a certain characteristic of the membership degree and the pattern of innovation: "very high", the interval of values of the membership function $\mu(A)x \leq 0,75 \leq \mu(A)x \leq 1$, pattern 1; "high", the interval of values of the membership function $0,5 \leq \mu(A)x < 0,75$, pattern 2; average, interval of values of the membership function $0,25 < \mu(A)x < 0,5$, pattern 3; low, interval of values of the membership function $0,1 \leq \mu(A)x \leq 0,25$, pattern 4. Based on the membership function, the authors have established the values of the set of values for the level of innovativeness, which are in the range from 1 to 9, corresponding to the highest membership degree for innovation patterns: pattern 1 – 9, pattern 2 – 6, pattern 3 – 4, pattern 4 – 2.

In order to assess innovation patterns and their significance for a concrete enterprise as part of the development of its innovation strategy, it is necessary to perform a regression analysis reflecting the dependence of the main indicators of the enterprise characterizing its economic growth on the level of innovativeness of the innovation projects being implemented. The authors highlight these indicators as being value added by the enterprise, labour productivity, market share and capital intensity of production. The value added depends on the profit of the enterprise associated with the purchase of its products; labour productivity is defined as the economic effect of the enterprise's activities per unit of labour, which can be both an employee of the enterprise and a man-hour; the measure of economic effect can also be understood as value added. For the purposes of this paper, a method is adopted for determining labour productivity as a quotient by dividing the value added of an enterprise by the number of employees. In this context, labour productivity is related to the demand for manufactured products to the same extent as value added is related to it. Market share is the percentage of an enterprise's sales of total industry or market sales; for an industrial enterprise, market share is the percentage of that enterprise's sales of that industry's sales, so higher demand for manufactured products results in a higher market share. The capital intensity of production in this paper is understood as an indicator that reflects the cost of capital investments for the production of a unit of output. Thus, this indicator represents the costs of the enterprise for the production of products. Assessing the impact of the level of innovation on each of these indicators in the context of choosing the optimal innovation pattern will allow us to evaluate the effectiveness of an enterprise's innovative activity, provided by the demand for innovative products corresponding to a particular innovation pattern, from the point of view of various aspects, in combination with an assessment of the costs of production, reflected capital intensity of production.

Following a regression analysis that reflects this dependence, it is necessary to determine on the basis of the obtained regression equations the value of each indicator characterizing the economic growth of an industrial enterprise that can be expected when implementing an innovation project with the highest membership degree for each innovation pattern. In other words, when implementing an innovation project with a level of innovativeness equal to 9, 6, 4 and 2. The values of indicators characterizing the economic growth of an enterprise – value added, labour productivity, market share and capital intensity of production – provided by the value of the indicator of innovativeness reflecting the highest membership degree for each individual innovation pattern, according to the regression equation obtained, are considered by the authors as the values of these indicators provided by a specific pattern. These values are taken as input data when analysing innovation patterns in order to select the most preferred pattern when forming an innovative strategy for an enterprise based on the proposed methodology. Since these values are obtained from regression equations, an important condition for their use as input data is the statistical significance of the parameters of the corresponding regression equations at a level not lower than $p < 0.5$, accepted for economic calculations, since only in this case such data can be considered reliable.

When developing a methodology for choosing the most preferred innovation pattern based on the analysis of such data, the authors proceed from the following considerations. Since the choice of the innovation pattern is supposed to be based on the evaluation of several criteria, such a choice requires the use of multiple-criteria decision-making methods, while the decision associated with this choice will be made under conditions of uncertainty and risk inherent in innovation and accompanying decisions within its framework, as well as the unequal significance of each of the criteria in different decision-making situations. It follows from this that decision-making on the choice of an innovation pattern should be carried out using methods based on determining the significance of each criterion, characterized by weight indicators, as well as taking into account possible losses not only within the framework of the decision-making procedure itself but also within the framework of determining the weight (significance) of each evaluated criterion. At the same time, when making a decision under conditions of uncertainty and risk, a detailed assessment of alternatives carried out in various ways is advisable, which will increase the adequacy of the assessment.

The advantages of the proposed methodology, in comparison with the existing methods of multiple-criteria decision-making, are the following:

1. A detailed analysis of alternatives according to all evaluated criteria by combining the determination of the closeness of each alternative (innovation pattern) to the ideal alternative with a pairwise comparison of alternatives, which is important when making a decision in conditions of uncertainty and risk. There are examples in the literature of combining the TODIM method, focused on pairwise comparison of alternatives, taking into account the significance of losses, with methods focused on finding the distance of alternatives from the ideal solution – the TOPSIS method (Khamseh, Mahmoodi, 2014; Lourenzutti, Krohling, Reformat, 2017; Liu, Liu, Wang, 2019; Liu, Luo, Liu, 2020) and the VIKOR method (Huang, Lin, Chen, 2019; Arya, Kumar, 2020; Arya, Kumar, 2021). At the same time, there is an example of using the VIKOR method taking into account the risk attitude of the decision-maker (Tavana, Di Caprio, Santos-Arteaga, 2018). However, the TOPSIS and VIKOR methods are limited in their application because they require compliance with certain conditions, in particular, the same ranking of alternatives by all evaluation results (TOPSIS method – by distance from positive ideal solution, distance from negative ideal solution and relative closeness to positive ideal solution, and VIKOR method – by group utility – the preference of an alternative according to most criteria, individual regret – losses according to the criterion by which they are most significant when choosing a certain alternative, and the VIKOR index, which is an overall index), which is not always possible to observe. Grey relational analysis, when determining the distance of each alternative from an ideal alternative, does not require additional conditions to be met. Moreover, this method, being based on the theory of grey systems designed for analysis under conditions of uncertainty and incomplete data, is more applicable compared to other methods of multi-criteria decision-making that are focused on finding the distance from an ideal solution and are suitable for making decisions concerning the innovation strategy of the industrial enterprise, which are associated with uncertainty and risk.

2. The proposed methodology will allow taking into account the losses associated with the choice of each alternative, both directly in the decision-making process on the choice of the innovation pattern, and when calculating the weights of the evaluated criteria, which is extremely relevant when making decisions in conditions of uncertainty and risk.

3. When making decisions on the choice of an innovation pattern within the framework of the development of an innovation strategy for an industrial enterprise, grey relational analysis and the TODIM method can be considered as complementary methods, since the TODIM method makes it possible to supplement the results of grey relational analysis by indicating the closeness of each alternative (innovation pattern) to the ideal alternative. This is achieved by a pairwise comparison of alternatives, taking into account the significance of losses related to the choice of each alternative based on the attenuation factor of losses θ, which also reflects the degree of risk. These provide details and concretization of the assessment of alternatives in the decision-making process, while grey relational analysis will create an objective basis for establishing the coefficient θ within the framework of the TODIM method, which will contribute to a more accurate, objective and adequate assessment.

Thus, it can be argued that the application of the proposed methodology when choosing an innovation pattern as part of the development of an industrial enterprise's innovation strategy will allow for a more detailed assessment of alternatives according to all evaluated criteria. To a large extent, it would also account for possible losses when choosing an alternative, as well as combine the capabilities of grey relational analysis based on the search for an alternative closest to the ideal alternative. The TODIM method, based on a pairwise comparison of alternatives, takes into account the significance of the losses associated with the choice of each alternative in order to make a decision with the least risk.

3 Data and methodology

The algorithm of application of the proposed technique consists of four consecutive stages, each of which contains an ordered sequence of actions.

Stage 1. Assessment of the innovativeness of earlier implemented innovative projects and the establishment of the values of economic indicators of an industrial enterprise characterizing its economic growth, provided by each innovation pattern.

1.1. Assessment of the innovativeness of innovative projects implemented earlier by an industrial enterprise, in accordance with formula (1).

1.2. Performing a regression analysis of the dependence of each economic indicator of an industrial enterprise characterizing its economic growth – value added, labour productivity, market share and capital intensity of production – on the level of innovativeness, based on the data obtained on the innovativeness of each earlier implemented innovative project and comparing them with these indicators.

1.3. Evaluation of the statistical significance of the parameters of the obtained regression equations.

1.4. Determination based on the obtained regression equations of the values of indicators characterizing the economic growth of the enterprise, achieved with the highest membership degree for each pattern of innovation, according to the membership function, i.e. the values of each of these indicators that can be expected at the level of innovativeness equal, respectively, 2, 4, 6 and 9, in accordance with a regression equation reflecting the dependence of a particular indicator on the level of innovativeness.

1.5. Drawing up a decision matrix in the form of a table consisting of the values of indicators characterizing the economic growth of an industrial enterprise, achieved with the highest membership degree for each innovation pattern.

Stage 2. Determination of the weight of each evaluated criterion (an indicator characterizing the economic growth of an enterprise) using the IDOCRIW method.

2.1. Determination of weights of criteria by the entropy method.

2.1.1. Normalization of the values of the decision matrix in accordance with the formula (2):

$$\tilde{r}_{ij} = \frac{r_{ij}}{\sum_{i=1}^{n} r_{ij}} \qquad (2)$$

where r_{ij} are the initial values of the decision matrix; $\tilde{r}_{ij}$ are the normalized values of the decision matrix, i is the number of the alternative (innovation pattern), i =1,...,n, j is the criterion number, j = 1,…, m. In this article, the following criteria numeration is used: value added – 1, productivity labour – 2, market share – 3, capital intensity of production – 4.

2.1.2. Calculation of entropy E_j for each j criterion (3):

$$E_j = -\frac{1}{\ln n}\sum_{i=1}^{n} \tilde{r}_{ij} * ln\, \tilde{r}_{ij} \qquad (3)$$

where n is the number of evaluation objects (alternatives), in th
is case, the number of innovation patterns, thus n = 4.

2.1.3. Calculation of the degree of variation (Zavadskas, Podvezko, 2016) (variation level (Chereshka, Podviezko, Zavadskas, 2018; Dayyani et al., 2021)) for each j-criteria d_j (4):

$$d_j = 1 - E_j \qquad (4)$$

2.1.4. Calculation of weights of criteria as normalized values of d_j (5):

$$W_j = \frac{d_j}{\sum_{j=1}^{m} d_j} \qquad (5)$$

where m is the number of criteria.

2.2. Determination of weights of criteria by the SILOS method.

2.2.1. Transformation of criteria requiring minimization into maximized criteria. Since the CILOS method can only be applied to maximized values of criteria (Cereska, Podviezko, Zavadskas, 2018), it is necessary to convert minimized values to maximized ones. The most applicable for this purpose is the inverse transformation (Čereška, Podviezko, Zavadskas, 2018), carried out according to the following formula (6):

$$\hat{r}_{ij} = \frac{min_i r_{ij}}{r_{ij}} \qquad (6)$$

The values obtained as a result of such a transformation (6) are normalized in a similar way to the normalization of values when determining the weight by the entropy method (Alinezhad, Khalili, 2019; Ali et al., 2020; Luo et al., 2021), in accordance with the formula (2). The values of the maximized criteria do not require transformation; therefore, the normalized values of these criteria are identical to the normalized values used in determining the weight by the entropy method, calculated by the formula (2). The matrix $X = \|x_{ij}\|$ is formed in the form of a table, the elements of which are the normalized values of the maximized criteria and the normalized values of the criteria requiring minimization obtained after transformation in accordance with formula (6). In the context of this study, there is one criterion requiring minimization – capital intensity of production.

2.2.2. Building a square matrix $A = \|a_{ij}\|$, $a_{ij} = x_{k_{ij}}$, $a_{jj} = x_j$, $x_j = max_i\, x_{ij}$, based on the values of the matrix $X = \|x_{ij}\|$. In the matrix $A = \|a_{ij}\|$, the rows correspond to alternatives (in this case, innovation patterns), and the columns correspond to criteria. k_j is the row number with the element of column j (column corresponding to criterion j) of the matrix $X = \|x_{ij}\|$, having the highest value (Zavadskas, Podvezko, 2016; Podvezko, Kildienė, Zavadskas, 2017; Trinkūnienė et al., 2017), then $x_{k_{ij}}$ are the values of the row of the matrix X, corresponding to the maximum value of the j-criterion. A method of forming a matrix $A = \|a_{ij}\|$ requires the following: the maximum of all the i-alternatives normalized values of each of the j-criterion in the matrix $X = \|x_{ij}\|$ entered into the matrix $A = \|a_{ij}\|$ on the main diagonal and accordingly moved the row of the matrix $X = \|x_{ij}\|$ in which these values are located. In other words, when placing the maximal normalized values of the criteria along the main diagonal of the matrix $A = \|a_{ij}\|$ the values that were in row with them in the matrix $X = \|x_{ij}\|$ are put in the same row with them. In general, according to the authors, the matrix $A = \|a_{ij}\|$ can be represented in the following form (7):

$$A = \begin{bmatrix} max_i\, x_{i1} & x_{k_{i2}} & \dots & x_{k_{im}} \\ x_{k_{i1}} & max_i\, x_{i2} & \dots & x_{k_{im}} \\ \vdots & \vdots & \ddots & \vdots \\ x_{k_{i1}} & x_{k_{i2}} & \dots & max_i\, x_{im} \end{bmatrix} \quad (7)$$

2.2.3. Construction of the matrix of relative losses of the impact of criteria (further – matrix of relative loss) $P = \|p_{ij}\|$. The matrix of relative loss, also called the matrix of the relative loss of criteria significance (Podvezko, Kildienė, Zavadskas, 2017; Trinkūnienė et al., 2017; Alao et al., 2021), is compiled according to the following formula (8):

$$p_{ij} = \frac{a_{jj} - a_{ij}}{a_{jj}} \quad (8)$$

or (9):

$$p_{ij} = \frac{x_j - a_{ij}}{x_j} \quad (9)$$

In other words, when forming a matrix of relative loss $P = \|p_{ij}\|$ from each of the maximum normalized values of the criterion, denoted as x_j or a_{jj}, located along the main diagonal of the matrix $A = \|a_{ij}\|$ each of the values in the corresponding column is subtracted, and after each such subtraction, the difference is divided by this the maximum normalized value of x_j (a_{jj}). The matrix $P = \|p_{ij}\|$ shows how much of the significance should be lost by each criterion of the alternative for it to be evaluated the best based on all the criteria (the optimum according to the Pareto principle) (Podvezko, Kildienė, Zavadskas, 2017 m.).

2.2.4. Compilation of the weight system matrix (Weight System Matrix) F. The weight system matrix has the following form (10):

$$F = \begin{bmatrix} -\sum_{i=1}^{n} p_{i1} & p_{12} & \dots & p_{1m} \\ p_{21} & -\sum_{i=1}^{n} p_{i2} & \dots & p_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ p_{m1} & p_{m2} & \dots & -\sum_{i=1}^{n} p_{im} \end{bmatrix} \quad (10)$$

Since the weight system matrix is a square matrix $m \times m$, the numbers of both criteria and alternatives corresponding to their number are denoted identically as m.

2.2.5. Determination of weights of criteria $q = (q_1, q_2, \dots, q_m)$. The weights of the criteria, in accordance with the CILOS method, are determined based on the solution of the system of equations (11):

$$Fq = 0 \quad (11)$$

As a result, a homogeneous system of equations is obtained, which, from the point of view of linear algebra, has an infinite set of solutions. The weight vector is found using linear programming (simplex method) by optimizing the objective function $\sum q_j = 1$ under conditions of constraints reflected by the system of equations (11). At the same time, in the works of recent years (Ali et al., 2020; Alto et al., 2021), a different method for determining the weight vector using the CILOS method is also presented within the framework of the IDOCRIW method (12):

$$q_j = F^{-1}A \quad (12)$$

where F^{-1} is the inverse matrix with respect to the weight system matrix F, A is a vector whose first element has a value close to 0, for example, 0.29 (Ali et al., 2020), 0.0001 (Alao, Popoola, Ayodele, 2021), and so on, and the remaining values are 0. The value of the first element of the nonzero vector is selected in such a way that the sum q_j is as close as possible to 1. When negative numerical values are obtained in the weight vector, the moduli of these numbers are taken as the values of the weights of the corresponding criteria. In accordance with the rule of matrix multiplication, this vector is written as a column-vector (column matrix), the number of elements (rows) in which should be equal to the number of columns of the matrix F^{-1}, in other words, to the number of criteria to be evaluated. However, the application of this method is possible only if the determinant of the matrix F is not equal to 0, since only in this case the matrix can have an inverse matrix. The calculations carried out by the authors show that in a number of cases when the determinant of the matrix F is 0; the simplex method finds the values of the weights of the criteria q_j and, conversely, in cases when using the simplex method it is not possible to find an acceptable solution, the weight vector is determined by the formula (12). Thus, these two methods are complementary.

2.3. Determination of the single overall weight in accordance with the formula (13):

$$w_j = \frac{q_j W_j}{\sum_{j=1}^{m} q_j W_j} \quad (13)$$

where W_j is the weight of the criterion calculated by the entropy method.

Stage 3. Determining the distance of each innovation pattern from the ideal alternative based on grey relational analysis.

3.1. Normalization of the values of the decision matrix in accordance with the rules of grey relational analysis. In the framework of grey relational analysis, the criterion number is denoted by k, $k = 1,\ldots, m$. When using grey relational analysis to evaluate alternatives (in this case, innovation patterns) in order to determine the alternative (innovation pattern) closest to the ideal alternative, the normalization of the values of the decision matrix is carried out in accordance with the following rule: if the criterion requires maximization (is a maximized criterion), the normalized values of $x_i^*(k)$ are calculated according to the following formula (14):

$$x_i^*(k) = \frac{x_i^o(k) - minx_i^o(k)}{maxx_i^o(k) - minx_i^o(k)} \qquad (14)$$

where $x_i^o(k)$ is the value of the initial data according to the k – criterion for the i-alternative; $min\ x_i^o(k)$ is the minimum value $x_i^o(k)$; $max\ x_i^o$ is the maximum value of $x_i^o\ (k)$.

If the criterion requires minimization, the normalized values of $x_i^*(k)$ are calculated using the following formula (15):

$$x_i^*(k) = \frac{maxx_i^o(k) - x_i^o(k)}{maxx_i^o(k) - minx_i^o(k)} \qquad (15)$$

3.2. Determination of the basic normalized values for all criteria (normalized reference series) $x_0^*(k)$, with which other values $x_i^*(k)$ are compared. The basic normalized values meet the condition $max\ x_i^*(k)$.

3.3. Calculation of the grey relational coefficient $\xi_i\ (k)$. The grey relational coefficient characterizes the closeness of the alternative (in this case, the innovation pattern) to the ideal alternative according to the k-criterion. This coefficient is calculated by the formula (16):

$$\xi_i(k) = \frac{\Delta min + \rho \Delta max}{\Delta_{0,i}(k) + \rho \Delta max} \qquad (16)$$

where (17, 18, 19):

$$\Delta_{0,i}(k) = \|x_0^*(k) - x_i^*(k)\| \qquad (17)$$

$$\Delta min = \min_{\forall j \in i} \min_{\forall k,} \|x_0^*(k) - x_i^*(k)\| \qquad (18)$$

$$\Delta max = \max_{\forall j \in i} \max_{\forall k} \|x_0^*(k) - x_i^*(k)\| \qquad (19)$$

In other words, Δmin represents the minimum value of $\Delta_{0,i}\ (k)$ among the values of all criteria for all alternatives, and Δmax means the maximum value of $\Delta_{0,i}\ (k)$ among the values of all criteria for all alternatives. The coefficient ρ is a distinguished coefficient, which is expressed as the contrast between the background and the object to be tested. This coefficient can be set by the decision-maker during the evaluation process. As a rule, ρ is assumed to be 0.5, because this value offers moderate distinguishing effects and good stability (Jiang et al., 2002; Lin et al., 2007; Sarraf, Neyad, 2020). However, some papers propose a method for determining the optimal value of the coefficient ρ (Feng, 1997; Luo, Li, 2013). The basis of this technique is the establishment of the coefficient ρ depending on the degree of fluctuation of the values of the analysed system, which in this case is considered a set of evaluated criteria. Fluctuations in the values of the criteria, in other words, differences in their values for different alternatives, are reflected by the indicators $\Delta_{0,i}(k)$, and Δmax characterizes the highest fluctuation of the values of the system. If the values of subject are undergoing to significant fluctuations, i.e. the alternatives differ greatly according to the criteria being evaluated, then $\rho\Delta max$ will be significantly higher than individual $\Delta_{0,i}(k)$, in this situation, all values of the grey relational grade, which is a ranked indicator in grey relational analysis, will be close to 1, reducing the reliability of the results analysis. In this case, a lower value of ρ should be set to mitigate the influence of fluctuations (differences between alternatives according to the criteria being evaluated). If the system is subject to single fluctuations and its elements (the evaluated criteria) are relatively stable, i.e. the difference between the alternatives according to the evaluated criteria is insignificant, then it is necessary to set a higher value of ρ, since in this situation, with a low value of the distinguished coefficient $\rho\Delta max$, it will be significantly lower than individual $\Delta_{0,i}(k)$, and the values of the grey relational grade will also be low; as a result, the integrity of the analysed system may not be fully reflected. Based on this, in the work (Feng, 1997), it is proposed to establish the coefficient ρ based on the indicator $\in_\Delta$, which is the ratio between the average value $\Delta_{0,i}(k)$ and Δmax (20):

$$\in_\Delta = \frac{\Delta_y}{\Delta max} \qquad (20)$$

where Δ_y is the average value of $\Delta_{0,i}(k)$, calculated by the formula (21):

$$\Delta_y = \frac{1}{n*m}\sum_{i=1}^{n}\sum_{k=1}^{m} x_0(k) - x_i(k) \qquad (21)$$

Thus, according to this methodology, the value of the coefficient ρ must satisfy the conditions (22, 23, 24)

$$\in_\Delta \leq \rho \leq 2 \in_\Delta \qquad (22)$$
$$\Delta max > 3\Delta_y, \in_\Delta \leq \rho \leq 1{,}5 \in_\Delta \qquad (23)$$
$$\Delta max \leq 3\Delta_y, 1{,}5 \in_\Delta < \rho \leq 2 \in_\Delta \qquad (24)$$

Based on these conditions, in the work (Feng, 1997), it is proposed to set the value of the coefficient ρ in the following way: if $\Delta max > 3\Delta_y$, $\rho = 1{,}5\in_\Delta$, if $\Delta max < 3\Delta_y$, $\rho = 2\in_\Delta$. At the same time, the calculation of the grey relational coefficient and grey relational grade with different values of ρ is proposed, the value providing the greatest distance between the maximum and minimum values of grey relational grade, determined by the difference between them, is considered as the most relevant value. Feng (1997) shows an example of a situation where such a distance is provided when determining the coefficient ρ based on this technique.

From the point of view of the authors, detailed analysis and accuracy in determining the value of the coefficient ρ are of particular importance when making a decision in conditions of uncertainty and risk, an example of which is the decision to choose an innovation pattern, due to the fact that any innovation activity is associated with uncertainty and risk, while different innovation patterns differ in the degree of risk. It is important in this situation to use the value of ρ, which provides the greatest distance between the maximum and minimum values of the grey relational grade, since such a distance will allow the most clearly ranking alternatives (innovation patterns) in closeness to the ideal alternative and highlight the innovation pattern closest to the ideal alternative, which in this respect has a clear difference from other patterns. However, the calculations carried out by the authors show that the presented method of determining the coefficient ρ does not always provide the greatest distance between the maximum and minimum values of the grey relational grade. In some cases, $\rho = 0.5$ provides a greater distance. Considering that the value of $\rho = 0.5$ reflects the stability and moderation of the difference between the basic normalized value $x_0^*(k)$ and other normalized values according to each criterion, when using grey relational analysis in the evaluation of innovation patterns, in order to most adequately establish the value of ρ and calculate the grey relational coefficient and grey relational grade, the distance should be compared between the maximum and minimum values of the grey relational grade obtained by using the coefficient ρ, set in accordance with the conditions: $\Delta max > 3\Delta_y$, $\rho = 1{,}5\in_\Delta$, $\Delta max < 3\Delta_y$, $\rho = 2\in_\Delta$, and the distance between the maximum and minimum values of the grey relational grade obtained at $\rho = 0.5$, and use the value of ρ, that provides the largest such distance.

3.4. Calculation of the grey relational grade γ_i for each alternative (innovation pattern) in accordance with formula (25) and determination of the innovation pattern closest to the ideal alternative.

$$\gamma_i = \sum_{k=1}^{m} w_k \, \xi_i(k) \qquad (25)$$

where $w_k = w_j$ is the single overall weight of the criterion determined on the basis of the IDOCRIW method.

The innovation pattern closest to the ideal alternative meets the condition of $max\ \gamma_i$.

Stage 4. Determining the most preferred innovation pattern based on the TODIM method.

4.1. Determination of the relative weight of each criterion, according to the formula (26):

$$\widetilde{w}_k = \widetilde{w}_j = \frac{w_j}{max\, w_j} \qquad (26)$$

where w_j is the single overall weight of the criterion determined on the basis of the IDOCRIW method.

4.2. Calculation of the dominance of each alternative over each other alternative for each k-criterion in accordance with the formula (27):

$$\phi_k(A_i, A_{i'}) = \begin{cases} -\frac{1}{\theta}\sqrt{\frac{\left(\sum_{j=1}^{m}\widetilde{w}_k\right)|\xi_i(k)-\xi_{i'}(k)|}{\widetilde{w}_k}} \text{ если } \xi_i(k) - \xi_{i'}(k) < 0 \\ 0 \text{ если } \xi_i(k) - \xi_{i'}(k) = 0 \\ \sqrt{\frac{\widetilde{w}_k\left(\xi_i(k)-\xi_{i'}(k)\right)}{\left(\sum_{j=1}^{m}\widetilde{w}_k\right)}} \text{ если } \xi_i(k) - \xi_{i'}(k) > 0 \end{cases} \qquad (27)$$

where $\xi_i(k)$ is the grey relational coefficient reflecting the distance of the innovation pattern from the ideal alternative on the each criterion, calculated within the framework of grey relational analysis; i is the number of the alternative

(innovation pattern); i' is the number of the alternative (innovation pattern) with which the i-alternative (innovation pattern) is compared; $|\xi_i(k) - \xi_{i'}(k)|$ is the modulus of the number obtained by subtracting $\xi_{i'}(k)$ from $\xi_i(k)$; θ is the attenuation factor of losses, $\theta > 0$. The attenuation factor of losses θ is set by the decision-maker, depending on his attitude to risk or depending on the level of risk accompanying the decision. A lower value of θ indicates a higher degree of loss aversion by the decision-maker (Li et al., 2015; Li, Fang, Song, 2019; Lu, Gao, Zhao, 2020;), while greater the θ lower is the degree of loss aversion (Zheng, Wang, Zhang, 2020). If $0 < \theta < 1$, the impact of losses on decision-making increases, if $\theta > 1$, the impact of losses on decision-making decreases (Qin, Liu, Pedricz, 2017; Davoudabadi, Mousavi, Mohagheghi, 2020; Kazancoglu et al., 2020). In other words, if the value $\theta > 1$ is set, then the decision-maker strives to choose an alternative with the maximum benefit, even if there will be tangible losses according to certain criteria, if $\theta < 1$, then the decision-maker chooses the alternative with the least losses according to all the evaluated criteria (Xie et al., 2019; Abadi, Nasab, Soleimani, 2020). Wang, Wang, Martínez (2020) characterize individual values of θ: if $\theta = 0.1$, then the decision-maker shows the highest risk aversion, if $\theta = 1$, then the decision-maker takes a neutral position, i.e. the significance of risk and the significance of winning are equivalent for him, if $\theta = 2$, then risk aversion is lower than neutral, if $\theta = 10$, then the decision-maker does not pay significant attention to smoothing the negative effect caused by losses.

In the process of making a decision on the choice of an innovation pattern, from the authors' point of view, the value of the attenuation factor of losses θ should be set in accordance with which innovation pattern is closest to the ideal alternative, corresponding to the results obtained from grey relational analysis. At the same time, it should be noted that two patterns of innovation – pattern 1 and pattern 2 – refer to radical innovations, while the other two patterns – pattern 3 and pattern 4 – to improving innovations. The first two patterns are characterized by a higher risk and the last two by a lower risk. If one of the innovation patterns related to radical innovations is closest to the ideal alternative, the value of θ should be set in the range $0< \theta <1$, since these patterns are associated with increased risk while the benefits cannot be fully estimated due to significant uncertainty. Pattern 3, due to its focus on already used for a long period of time and proven technologies (core technologies), on the basis of which products were produced that are in demand in the market, has significantly less risk compared to patterns 1 and 2. However, the creation of a new market is associated with significant risk, while the risk is offset by the possibility of the enterprise to return to the previous market and/or maintain their positions on it. Since within the framework of pattern 3, technologies are used with respect to which the enterprise has considerable experience, the results of creating and implementing innovations of such a pattern are quite predictable. From this, it can be concluded that in the case of pattern 3, equal attention should be paid to possible losses and possible benefits. Therefore, if the results of grey relational analysis show that pattern 3 is close to the ideal alternative, the value of θ should be set to 1. Pattern 4, which is based on the use of long-term and proven technologies (core technologies) for the gradual improvement of products sold in the existing market, is predictable in the field of obtaining benefits and is characterized by a low level of risk. Therefore, a value of θ exceeding 1 should be set for this innovation pattern. At the same time, the authors believe that for a clear gradation of the various conditions for establishing the value of θ, it is necessary, if possible, to establish equal intervals of values of θ between patterns. To that end, the authors propose to set the values of the attenuation factor of losses θ equal to 0.5 and 0.75, respectively, in relation to patterns 1 and 2 related to radical innovations, in relation to pattern 3 it is 1, and in relation to pattern 4 it is 2. This value reflects risk aversion below neutral, in which $\theta = 1$, with a slight predominance of the significance of the benefits received over the significance of losses, which fully corresponds to pattern 4, which is the most predictable in terms of benefits and possible losses. But, like any innovation, it is characterized to some extent by the degree of uncertainty and risk, as a result of which it is impractical to set a value greater than 2 for it.

4.3. Calculation of the dominance degree of each alternative according to the formula (28):

$$\delta_i = \sum_{k=1}^{m} \phi_k (A_i, A_{i'}) \qquad (28)$$

4.4. Calculation of the overall dominance degree of each alternative ζi by the formula (29):

$$\zeta_i = \frac{\delta_i - min\delta_i}{max\delta_i - min\delta_i} \qquad (29)$$

4.5. Determination of the most preferred innovation pattern within the framework of the development of the innovation strategy of the enterprise. The most preferred pattern meets the condition $max\ \zeta_i$.

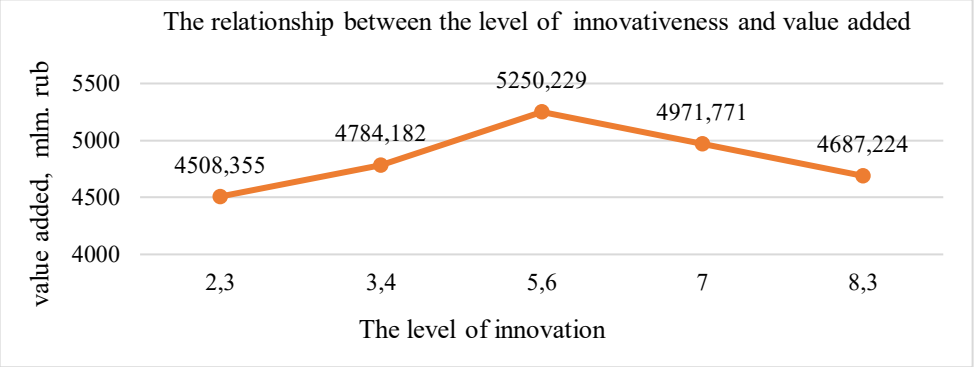
In order to test the proposed method of decision-making on the choice of the optimal pattern of innovation within the framework of developing the innovation strategy of the enterprise, we will carry out calculations on a conditional example. Let's assume that an industrial enterprise has implemented five innovative projects in seven years and wants to develop a further innovation strategy with the choice of the optimal innovation pattern based on this experience. The level of innovativeness of each of these projects was assessed. There was also an analysis of four economic indicators characterizing the economic growth of the enterprise after the implementation of each of these projects: value added, labour productivity, market share and capital intensity of production. The values of these indicators after the implementation of each of the innovative projects with a certain level of innovativeness are presented in Table 1. The numbers of innovative projects are indicated in the order of their implementation.

Table 1. Indicators of economic growth of the enterprise after the implementation of innovative projects with a certain level of innovation

Innovation project number	Level of innovativeness (*I*)	Value added, mln. rubles	Labour productivity, mln. rubles/person	Market share, %	Capital intensity of production, rubles
1	2.3	4508.355	2.925	34.45	2.53
2	3.4	4784.182	3.317	39.55	2.21
3	5.6	5250.229	3.757	42.25	1.95
4	7	4971.771	4.125	40.51	1.81
5	8.3	4687.224	3.808	39.01	1.73

Based on these data, a regression analysis was performed to reflect the impact of the level of innovativeness of projects on each of the four economic indicators characterizing the economic growth of the enterprise: value added, labour productivity, market share and capital intensity of production. Then, based on the regression equations obtained, the values of these indicators were calculated, which can be expected at the values of the level of innovativeness corresponding to the highest membership degree for each of the innovation patterns, that is, with the level of innovativeness equal to, respectively, 2, 4, 6 and 9. Figure 1 shows that the relationship between the level of innovativeness and the value added is expressed by a parabola, whose branches are directed downward. Therefore, a parabolic regression model was used for its analysis.

Fig. 1. The relationship between the level of innovation and value added



The following parabolic regression equation (30) was obtained: $y_x = 3150{,}035+724{,}689x\text{-}65{,}172x^2$ (30)

The standard errors of the regression parameters (30) were calculated, and the statistical significance of the parameters was evaluated by the Student's *t*-test. Parabolic regression is linear in the estimated parameters, the number of its parameters is greater than 2 and, in addition, the system of least squares equations (OLS) is similar to the system of OLS equations for multiple regression with three parameters and two explanatory variables. Therefore, the standard errors and values of the Student's *t*-test for regression parameters were determined in the same way as with multiple linear regression (31, 32, 33):

$$\hat{S}_{a_j} = \sqrt{\hat{S}^2_{a_j}}, \quad (31)$$

$$\hat{S}^2_{a_j} = \hat{S}^2[(X^TX)^{-1}]_{jj} \quad (32)$$

$$t_{a_j} = \frac{a_j}{\hat{s}_{a_j}} \quad (33)$$

where $\hat{S}_{a_j}$ is the standard error of the coefficient a_j; $\hat{S}^2_{a_j}$ is the variance of the regression coefficient a_j; $[(X^TX)^{-1}]_{jj}$ – elements of the inverse matrix standing on the main diagonal; t_{a_j} – the calculated value of the Student's *t*-test for the regression parameter a_j; $\hat{S}^2$– an unbiased estimator of the variance of the error determined by the formula (34):

$$\hat{S}^2 = \frac{1}{n-k-1}\sum_{i=1}^{n}(y_i - y_x)^2 \quad (34)$$

where *n* is the number of observations; *k* is the number of explanatory variables.

The following results are obtained: the standard errors of the regression parameters are equal to: $\hat{S}_{a_0}$= 293.6605, $\hat{S}_{a_1}$= 127.649, $\hat{S}_{a_2}$= 12.018, the values of the Student's *t*-test are t_{a0} = 10.727, t_{a1} = 5.677, t_{a2} = 5.423. The values of t_{a1} and t_{a2} exceed the critical value of t_k at a significance level of $p < 0.05$, while t_{a0} exceeds the critical value at a higher significance level of $p < 0.01$. Taking into account the significance level $p < 0.05$ accepted for economic calculations, the coefficients of the regression equation (32) can be considered statistically significant.

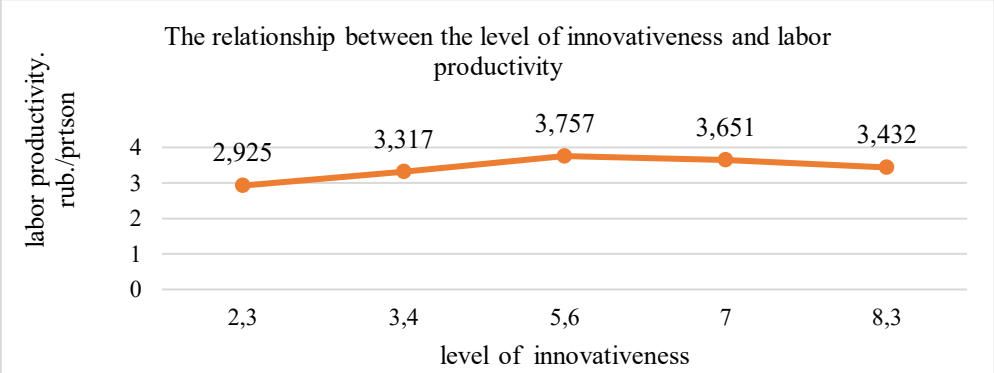
The extremum (maximum) of the function is (35):

$$x = -\frac{b}{2c} = \frac{-724.689}{-130.344} = 5.56 \qquad (35)$$

This value is in the range of values for the level of innovation corresponding to pattern 2, from which it can be concluded that, from the point of view of added value, the most preferred innovation pattern is pattern 2. The values of the level of innovativeness corresponding to the highest membership degree for each innovation pattern, according to the regression equation (30), provide the following values of added value: pattern 1 – 4393.271 million rubles; pattern 2 – 5151.961 million rubles; pattern 3 – 5006.031 million rubles; and pattern 4 – 4338.722 million rubles.

The relationship between the level of innovativeness and labour productivity, as shown in Figure 2, is also parabolic. So a parabolic regression model was used to analyse it.

Fig. 2. The relationship between the level of innovativeness and labour productivity



The following regression equation (36) was obtained: $y_x = 1.585+0.717x - 0.0597x^2$ (36)

The standard errors of the regression parameters (36) were calculated and the statistical significance of the parameters was evaluated according to the Student's *t*-test, in accordance with the formulas (31)–(34). The following results were obtained: $\hat{S}_{a_0} = 0.097$, $\hat{S}_{a_1} = 0.042$, $\hat{S}_{a_2} = 0.004$; $t_{a0} = 16.34$, $t_{a1} = 17.071$, $t_{a2} = 14.925$. The values of t_{a0}, t_{a1} and t_{a2} exceed the critical value of t_k at a significance level $p < 0.01$, which indicates the high statistical significance of all parameters of the regression equation (36).

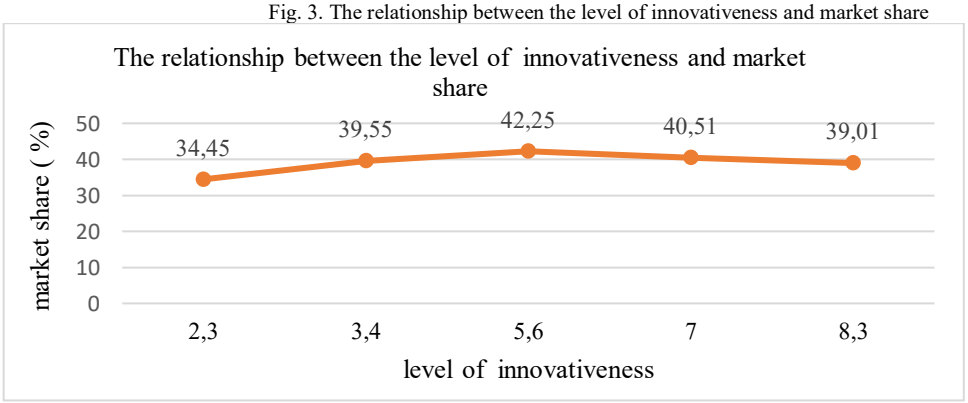
The extremum (maximum) of the function is (37):

$$x = -\frac{b}{2c} = \frac{-0.717}{-0.1194} = 6.005 \qquad (37)$$

This value is in the range of values for the level of innovativeness corresponding to pattern 2, which means that from the point of view of labour productivity, the most preferred pattern of innovation is pattern 2. The values of the level of innovativeness corresponding to the highest membership degree for each pattern of innovation, according to the regression equation (36), provide the following values of labour productivity: pattern 1 – 3.202 million rubles/person, pattern 2 – 3.738 million rubles/person; pattern 3 – 3.498 million rubles/person; pattern 4 – 2.781 million rubles/person.

The relationship between the level of innovativeness and market share is also expressed by a parabola, the branches of which are directed downward, as follows from Fig. 3. Therefore, a parabolic regression model was used for its analysis.

Fig. 3. The relationship between the level of innovativeness and market share



The following regression equation (38) was obtained:

$$y_x = 22.399+6.804x - 0.585x^2 \qquad (38)$$

The standard errors of the regression parameters were calculated (38), and the statistical significance of the parameters was evaluated by the Student's *t*-test, in accordance with the formulas (31)–(34). The following results were obtained: $\hat{S}_{a_0}$= 2.929, $\hat{S}_{a_1}$= 1.273, $\hat{S}_{a_2}$= 0.1199; t_{a0} = 7.647, t_{a1} = 5.345, t_{a2} = 4.879. The values of t_{a0}, t_{a1} and t_{a2} exceed the critical value of t_k at a significance level of $p < 0.05$. Taking into account the significance level $p < 0.05$ accepted for economic calculations, the coefficients of the regression equation (38) can be considered statistically significant.

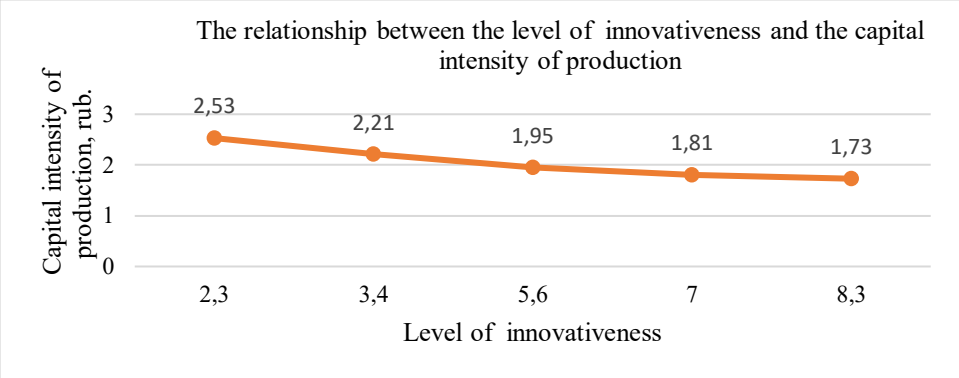
The extremum (maximum) of the function is (39):

$$x = -\frac{b}{2c} = \frac{-6.804}{-1.17} = 5.815 \qquad (39)$$

This value is in the range of values for the level of innovativeness corresponding to pattern 2. Thus, from the position of market share, as well as from the position of value added and labour productivity, the most preferred pattern of innovation is pattern 2. The values of the level of innovativeness corresponding to the highest membership degree for each pattern of innovation, according to the regression equation (38), the following market share values are provided: pattern 1 – 36.23%, pattern 2 – 42.15%, pattern 3 – 40.25%, pattern 4 – 33.67%.

The relationship between the level of innovativeness and the capital intensity of production is expressed by a hyperbola reflecting the inverse relationship, which is shown in Fig. 4. Therefore, a hyperbolic regression model was used for its analysis. An additional argument in favour of this model is the impossibility of reducing the capital intensity of production to zero, which necessitates the use of a regression model reflecting a slow decrease in the dependent variable with an increase in the explanatory variable, continuing to a certain limit.

Fig. 4. The relationship between the level of innovativeness and capital intensity of production.



The following regression equation (40) was obtained:

$$y_x = 1.463 + 2.489\frac{1}{x} \qquad (40)$$

The standard errors of the regression parameters (40) were calculated, and the statistical significance of the parameters was evaluated by the Student's *t*-test. Since hyperbolic regression is linear in terms of the estimated parameters, the authors believe that the formulas used for paired linear regression (41)–(44) should be used to calculate the standard errors and values of the Student's *t*-test within the framework of this regression model:

$$\hat{S}_{a_0} = \sqrt{\frac{\hat{S}^2 \sum_{i=1}^{n} x_i^2}{n\sum_{i=1}^{n} x_i^2 - \left(\sum_{i=1}^{n} x_i\right)^2}} \qquad (41)$$

$$\hat{S}_{a_1} = \sqrt{\frac{\hat{S}^2}{\sum_{i=1}^{n}(x_i - \bar{x})^2}} \qquad (42)$$

$$t_{a_0} = \frac{a_0}{\hat{s}_{a_0}} \qquad (43)$$

$$t_{a_1} = \frac{a_1}{\hat{s}_{a_1}} \qquad (44)$$

where $\hat{S}_{a_0}$ is the standard error of the coefficient a_0, $\hat{S}_{a_1}$ is the standard error of the coefficient a_1, n is the number of observations, $\hat{S}^2$ is an unbiased estimator of the variance of the error (45):

$$\hat{S}^2 = \frac{1}{n-2}\sum_{i=1}^{n}(y_i - y_x)^2 \qquad (45)$$

The following results were obtained: S_{a_0}= 0.039, S_{a_1}= 0.007; t_{a0} = 37.51, t_{a1} = 355.57. The values of t_{a0} and t_{a1} exceed the critical value of t_k at a significance level of $p < 0.01$, which indicates a high statistical significance of the

parameters of the regression equation. The authors also calculated the values of the Student's *t*-test for regression parameters a_0 and a_1 in accordance with the formulas used for various types of paired regressions (46, 47):

$$t_{a_0} = a_0 \frac{\sqrt{n-2}}{\sigma_\varepsilon} \quad (46)$$

$$t_{a_1} = a_1 \frac{\sqrt{n-2}}{\sigma_\varepsilon} \sigma_x \quad (47)$$

where σ_x is the mean square deviation of the explanatory variable x_i from the general mean x (standard deviation x), σ_ε is the mean square deviation of the dependent variable y_i from the aligned values y_x, calculated by the formula (48):

$$\sigma_\varepsilon = \sqrt{\frac{\sum_{i=1}^{n}(y_i - y_{x_i})^2}{n}} \quad (48)$$

The following results were obtained: t_{a0} = 96.9298, t_{a1} = 365.691. Thus, the values of the Student's *t*-test calculated on the basis of formulas (46)–(48) also exceed the critical value of t_k at a significance level of $p < 0.01$ and indicate a high statistical significance of the regression parameters. The value of the Student's *t*-test in relation to parameter a_1, which is the most important regression parameter characterizing the slope of a straight line, obtained by applying formulas (46)–(48), is close to the value obtained based on the calculation of standard errors in accordance with formulas (41)–(45), which, according to the authors, indicates the adequacy of the calculation of standard errors and determination based on the statistical significance of the parameters of hyperbolic regression by the Student's *t*-test.

In hyperbolic regressions, the parameter a_0 is of great importance, which indicates the maximum level of increase or decrease of the dependent variable when the explanatory variable changes. Thus, a_0 = 1.463 means that with a further increase in the level of innovativeness towards pattern 1, we can expect a decrease in the capital intensity of production to 1,139 rubles, which implies that the most preferred pattern of innovation from the standpoint of capital intensity of production is pattern 1. According to the regression equation (40), the values of the level of innovativeness corresponding to the highest membership degree for each pattern provide the following values of the capital intensity of production: pattern 1 – 1.74 rubles, pattern 2 – 1.88 rubles, pattern 3 – 2.09 rubles, pattern 4 – 2.71 rubles.

4 Results and conclusions

To analyse innovation patterns according to all criteria characterizing the economic growth of an enterprise, in order to select the most preferred innovation pattern for the formation of a further innovation strategy for an industrial enterprise, the values of the evaluated criteria corresponding to the highest membership degree for each pattern are grouped and a decision matrix is compiled (Table 2). Within the framework of this work, the following designation of criteria is adopted: value added – 1, labour productivity – 2, market share – 3, capital intensity of production – 4.

Table 2. Decision matrix for choosing the innovation pattern

Innovation pattern	The values of criteria corresponding to the level of innovativeness with the highest membership degree to the innovation pattern obtained as a result of regression analysis			
	Added value, mln. rub.	Labour productivity, mln. rub./ person	Market share, %	Capital intensity of production, rub.
1	4393.271	3.202	36.23	1.74
2	5151.961	3.738	42.15	1.88
3	5006.031	3.498	40.25	2.09
4	4338.722	2.781	33.67	2.71

For the purpose of further analysis, the weight of each criterion was determined using the IDOCRIW method. The values in Table 4 were normalized in accordance with the formula (2), and based on the normalized values, weights were calculated using the entropy methods (3)–(5). The results obtained are presented in Table 3.

Table 3. Determination of weights of criteria by the entropy method

Innovation pattern	Normalized values of criteria			
	Added value	Labour productivity	Market share	Capital intensity of production
1	0.233	0.242	0.238	0.207
2	0.273	0.283	0.277	0.223
3	0.265	0.265	0.264	0.248
4	0.23	0.21	0.221	0.322
e_j	0.998	0.996	0.997	0.989
d_j	0.002	0.004	0.003	0.011
W_j	0.1	0.2	0.15	0.55

Next, the weights of the criteria were calculated using the SILOS method. Since among the evaluated criteria there is a criterion requiring minimization: for the capital intensity of production, a transformation was carried out in relation to this criterion in accordance with formula (6), followed by normalization of the obtained values according to formula (2), on the basis of which normalization was carried out within the framework of determining the weights of the criteria by the entropy method. The results are presented in Table 4.

Table 4. Matrix of normalized criteria values with transformation of criteria requiring minimization $X = \|x_{ij}\|$.

Innovation pattern	Normalized values of criteria			
	Added value	Labour productivity	Market share	Capital intensity of production
1	0.233	0.242	0.238	0.294
2	0.273	0.283	0.277	0.272
3	0.265	0.265	0.264	0.245
4	0.23	0.21	0.221	0.189

Based on the values of Table 4, a square matrix $A = \|a_{ij}\|$ was compiled. As applied to the present work, the square matrix $A = \|a_{ij}\|$ looks like this (49):

$$A = \begin{bmatrix} 0.273 & 0.283 & 0.277 & 0.272 \\ 0.273 & 0.283 & 0.277 & 0.272 \\ 0.273 & 0.283 & 0.277 & 0.272 \\ 0.233 & 0.242 & 0.238 & 0.294 \end{bmatrix} \quad (49)$$

The matrix of relative loss (p_{ij}) has the form (50):

$$P = \begin{bmatrix} 0 & 0 & 0 & 0.075 \\ 0 & 0 & 0 & 0.075 \\ 0 & 0 & 0 & 0.075 \\ 0.147 & 0.145 & 0.141 & 0 \end{bmatrix} \quad (50)$$

The weight system matrix (F) has the form (51):

$$F = \begin{bmatrix} -0.147 & 0 & 0 & 0.075 \\ 0 & -0.145 & 0 & 0.075 \\ 0 & 0 & -0.141 & 0.075 \\ 0.147 & 0.145 & 0.141 & -0.225 \end{bmatrix} \quad (51)$$

Thus, the following system of equations was obtained for determining the weights of the criteria (52):

$$\begin{cases} -0.147q_1 + 0.075q_4 = 0 \\ -0.145q_2 + 0.075q_4 = 0 \\ -0.141q_3 + 0.075q_4 = 0 \\ 0.147q_1 + 0.145q_2 + 0.141q_3 - 0{,}225q_4 = 0 \end{cases} \quad (52)$$

Since the determinant of the matrix F (51) is 0, this matrix does not have an inverse matrix, which excludes the possibility of using the method of determining the weight vector, in accordance with formula (10), as described in the previous works (Ali et al., 2020; Alao, Popoola, Ayodele, 2021). The only way to find the values of the weighted estimated criteria for the CILOS (q_j) method is through linear programming (simplex method). By optimizing the objective function $\sum q_j = 1$ under the constraints presented in the system of equations (52), using the Microsoft Excel program, the following values of the criteria weights were obtained using the CILOS method: $q_1 = 0.199$, $q_2 = 0.202$, $q_3 = 0.208$, $q_4 = 0.391$.

Based on the values of the criteria weights calculated by the entropy method and the CILOS method, a single overall weight for each criterion was established in accordance with formula (13). As a result, the following values were obtained: $w_1 = 0.065$, $w_2 = 0.132$, $w_3 = 0.102$, $w_4 = 0.701$.

After setting the weights of the criteria, the distance of each innovation pattern from the ideal solution was estimated based on grey relational analysis. In accordance with the formulas (14, 15), the normalization of criteria values was carried out. The results obtained are presented in Table 5.

Table 5. Normalized values of criteria, according to grey relational analysis.

Innovation pattern	Normalized values of criteria			
	Added value	Labour productivity	Market share	Capital intensity of production
1	0.067	0.44	0.302	1
2	1	1	1	0,856
3	0.821	0.749	0.776	0,639
4	0	0	0	0

Thus, $x_0^*(k)$ is equal to 1 for all criteria k. Based on the normalized values of the criteria obtained, in accordance with formula (17), the values of Δ_{0i} (k) were calculated, which are presented in Table 6.

Table 6. Values of Δ_{0i} (k).

Innovation pattern	Values Δ_{0i} (k)			
	Added value	Labour productivity	Market share	Capital intensity of production
1	0.933	0.56	0.698	0
2	0	0	0	0.144
3	0.179	0.251	0.224	0.361
4	1	1	1	1
	$\Delta_{min} = 0$			
	$\Delta_{max} = 1$			

The value of the coefficient ρ was determined in accordance with the approach to its determination presented in the algorithm of application of the proposed methodology (20)–(24):

$$\Delta_y = \frac{1}{n*m}\sum_{i=1}^{m}\sum_{k=1}^{n}|x_0(k) - x_i(k)| = \frac{\sum \Delta_{0i}(k)}{n*m} = 0.4594 \quad (53)$$

$$\in_{\Delta} = \frac{\Delta_y}{\Delta_{max}} = 0.4594 \quad (54)$$

$$3\Delta_y = 1.3782, \Delta_{max} < 3\Delta_y, \rho = 2 \in_{\Delta} = 0.9188 \quad (55).$$

After determining the coefficient ρ in accordance with the approach to establishing its optimal value, the grey relational coefficient ξ_i (k) (16) and the grey relational grade γ_i (25) were calculated, using both the obtained coefficient value ρ = 0.9188 and the coefficient value ρ = 0.5, in order to obtain the most accurate and adequate analysis results. The results are presented in Tables 7 and 8.

Table 7. Values of the grey relational coefficient $\xi_i(k)$ and the grey relational grade γ_i at ρ = 0,9188

ξ_i (k)	Criteria				γ_i at ρ = 0,9188
	Added value	Labour productivity	Market share	Capital intensity of production	
ξ_1 (k)	0.496	0.621	0.568	1	0.87315
$\xi_2(k)$	1	1	1	0.865	0.90537
$\xi_3(k)$	0.837	0.785	0.804	0.718	0.74335
$\xi_4(k)$	0.479	0.479	0.479	0.479	0.479

Table 8. Values of the grey relational coefficient $\xi_i(k)$ and the grey relational grade γ_i at ρ = 0,5

ξ_i (k)	Criteria				γ_i at ρ = 0,5
	Added value	Labour productivity	Market share	Capital intensity of production	
ξ_1 (k)	0.349	0.472	0.417	1	0.82852
$\xi_2(k)$	1	1	1	0.776	0.84298
$\xi_3(k)$	0.736	0.666	0.691	0.581	0.61352
$\xi_4(k)$	0.333	0.333	0.333	0.333	0.333

At $\rho = 2\in_{\Delta}$ = 0.9188 $\gamma_{i\,(max)} - \gamma_{i\,(min)}$ = 0.42637, whereas at ρ = 0.5 $\gamma_{i\,(max)}$-$\gamma_{i\,(min)}$ = 0.50998, from which it follows that at ρ = 0.5 the distance between the maximum and minimum values of the grey relational grade γ_i is greater compared to with $\rho = 2\in_{\Delta}$ = 0.9188, thus, at ρ = 0.5, the analysed system, which is a set of evaluated criteria, is more fully reflected, and alternatives are graded more clearly. Therefore, the values presented in Table 8 should be used as the values of $\xi_i(k)$ and γ_i.

After obtaining the results of the grey relational analysis, the TODIM method was applied in order to compare alternatives in pairs based on the values of their closeness to the ideal alternative for each of the criteria, which are the values of $\xi_i(k)$, taking into account the degree of risk. Grey relational analysis showed that the innovation pattern closest to the ideal alternative, in accordance with the values of the grey relational grade γ_i, is pattern 2. Thus, the value of the attenuation factor of losses was established as θ = 0.75. The values of the dominance of each alternative over each other alternative for each k-criterion ϕ_j $(A_i, A_{i'})$ at θ = 0.75 were calculated using the formula (27). The results are presented in Table 9.

Table 9. The values of the dominance of each alternative over each other alternative for each k-criterion ϕ_j $(A_i, A_{i'})$ at θ = 0,75.

A pair of alternatives		ϕ_j $(A_i, A_{i'})$			
		$\phi_1(A_i, A_{i'})$	ϕ_2 $(A_i, A_{i'})$	ϕ_3 $(A_i, A_{i'})$	ϕ_4 $(A_i, A_{i'})$
$A_{\sim}$	(A_1, A_2)	-4.214	-2.669	-3.183	0.396
	(A_1, A_3)	-3.249	-1.618	-2.182	0.542

	(A_1, A_4)	0.032	0.135	0.093	0.684
	(A_2, A_1)	0.206	0.264	0.244	-0.754
A_2	(A_2, A_3)	0.131	0.21	0.178	0.37
	(A_2, A_4)	0.208	0.296	0.261	0.557
	(A_3, A_1)	0.159	0.16	0.167	-1.031
A_3	(A_3, A_2)	-2.684	-2.123	-2.317	-0.703
	(A_3, A_4)	0.162	0.209	0.191	0.417
	(A_4, A_1)	-0.661	-1.37	-1.208	-1.3
A_4	(A_4, A_2)	-4.266	-3	-3.404	-1.06
	(A_4, A_3)	-3.316	-2.12	-2.494	-0.793

Based on formula (28), the values of the dominance degree of δ_i for each alternative were calculated: δ_1= -15.233, δ_2 = 2.171, δ_3 = -7.393, δ_4 = -24.992. The overall dominance degrees according to the formula (29) are ζ_1 = 0.359; ζ_2 = 1; ζ_3 = 0.648; ζ_4 = 0. Thus, the most preferred pattern of innovation for an enterprise is pattern 2: when planning a further innovation strategy, an enterprise should focus on radical innovations associated with the use of fundamentally new technologies, both by manufacturing fundamentally new products based on them and radically improving the quality of products; however, the production and sale of such products should be carried out within the existing market, taking into account the needs of the target customers related to this market.

The proposed approach will enable the selection of an innovation pattern within the framework of developing an innovative strategy for an industrial enterprise, taking into account both the proximity of each pattern to an ideal alternative and the advantages of each pattern, revealed when comparing them in pairs. In addition, the losses associated with the choice of each innovation pattern and their importance in the decision-making process are taken into account, which will allow a detailed assessment of all patterns of innovation. Then a pattern that maximizes demand for innovative products manufactured by the enterprise is chosen, which is reflected in demand-driven economic growth indicators – value added, labour productivity and market share, while minimizing the costs of producing these products, as determined by the capital intensity of production. At the same time, the application of this approach will help to reduce the opportunity costs of an industrial enterprise associated with the loss of profits when making a decision regarding the production of innovative products with a certain degree of novelty. Such a choice of an innovation pattern plays an important role in the development of an innovation strategy for an industrial enterprise, since the essence of innovation patterns covers a significant number of aspects of an innovation strategy. From this, we can conclude that the proposed methodology for choosing an innovation pattern will allow optimizing risks in the development of an innovation strategy and developing a strategy that ensures the effectiveness of an enterprise's innovation activity to the greatest extent. The technique can be used in any industry, but its application is most relevant in the latest high-tech industries, which are characterized by the active creation and implementation of innovations, such as the electronics industry, bioindustry, and nanotechnology, where, due to intensive development, it is problematic to focus on pattern 4, which is characterized by consistent and gradual innovative development and the lowest risk, and the emphasis on high-risk patterns is most characteristic. At the same time, the choice of pattern 1, which is characterized by the highest innovativeness, is not always appropriate in these industries, since the production of fundamentally new products produced using the latest technologies by virtue of which a new market is formed may not suit the conservative consumers who may prefer innovative and high-tech, but, at the same time, to a certain extent, familiar products. At the same time, the production of innovative products that meet pattern 1 can both help reduce the costs of the enterprise, due to the introduction of new technologies into the production process, and significantly increase its costs. This situation requires special care in choosing an innovation pattern, which requires a combination of assessing the proximity of each pattern to an ideal alternative and pairwise comparisons of patterns, taking into account the losses associated with the choice of each pattern.

The proposed methodology for choosing an innovation pattern is flexible and amenable to further improvement. The authors consider various directions for its modification depending on the specific situation. In the case of diversification of the innovative activity of an industrial enterprise with a focus on different market segments with different target audiences, it may be necessary to select two or three innovation patterns, while such a choice must also be made taking into account both the advantages and losses associated with the choice of each pattern. In this situation, it is advisable to use the MABAC method instead of the TODIM method along with grey relational analysis. The MABAC method is a multi-criteria decision-making method based on determining the distance of each alternative from the border approximation area based on a set of criteria, taking into account the weight of each of them. This method is based on the selection of three areas of approximation: the upper area of approximation (upper approximation area), the lower area of approximation (lower approximation area), the boundary area of approximation (border approximation area) and the determination of whether each alternative belongs to a particular area. The upper region of approximation is the region of ideal alternatives, while the lower region of approximation is the region of anti-ideal alternatives (Pamučar, Ćirović, 2015; Rahim, Abdullah, Yusuf, 2020). The authors believe that the upper approximation region can be characterized as a low-risk region, and the lower approximation region as a high-risk region. The use of the MABAC method together with grey relational analysis to select innovation patterns will allow us to select two or three patterns that are in the upper approximation area, which is a low-risk area, taking into account their proximity to the ideal alternative as the best alternative for all evaluated criteria, as determined by grey relational analysis. Thus, the innovative activity of an industrial enterprise is diversified while maintaining its position in the existing market segment

on the basis of maximizing demand for manufactured products and minimizing the costs associated with its production. Improving the methodology in this direction is especially important if, in accordance with the results obtained by its application, the optimal (most preferable) innovation pattern is one of the patterns characterized by low innovation (pattern 3 or pattern 4), while the enterprise has significant technological potential, allowing it to create innovative products that correspond to pattern 1 and/or pattern 2.

As another direction for improving the proposed methodology, the authors consider the determination of the weight of the criterion, carried out on the basis of a combination of the IDOCRIW method and the CRITIC method. The CRITIC method is based on determining the relationship of each criterion with other criteria, which is established using the apparatus of mathematical statistics: the correlation coefficient between each pair of criteria and the standard deviation of the criterion values for which the weight is calculated. This combination will allow you to set the weights of the criteria, taking into account both the dominance of each criterion and the losses for each criterion, as determined within the framework of the IDOCRIW method, and the relationship of each criterion with other criteria, identified by calculating the correlation coefficients in the process of applying the CRITIC method, which is relevant when evaluating innovation patterns according to the criteria presented in this article. The directions presented by the authors are considered as directions for future research.

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