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A new approach for determining weight coefficients of criteria within the scope of multi-criteria decision making: Logarithmic effect-based measurement (LEBM)

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Abstract

In the literature of multi-criteria decision making (MCDM), there are many methods related to the measurement of weight coefficients of criteria. In this study, a mathematical model based on the logarithmic effect among criteria (Logarithmic Effect-Based Measurement, LEBM) is proposed to contribute to the MCDM literature and to calculate the weight coefficients of criteria. The dataset used in the study consists of criterion values belonging to the Logistics Performance Index (LPI) of 18 countries in the G20 group. According to the analysis results, the proposed method is considered successful in calculating the objective weight coefficients of criteria for countries. Additionally, the proposed method is compared with other objective weighting methods (ENTROPY, CRITIC, SD, SVP, LOPCOW, and MEREC) within the scope of sensitivity analysis. The findings indicate that the rankings of LPI weight coefficients measured using the proposed method are similar to those measured using the MEREC method, and the relationship between the LPI weight coefficients determined using the proposed method and the MEREC method is positive, significant, and strong. Therefore, it is believed that the proposed method will contribute both to the logarithmic function and the MCDM literature

1. Introduction

Multi-criteria decision making is a method used in complex decision processes and mathematical modelling, where many factors are taken into account. In this process, the evaluation and ranking of alternatives based on decision-makers' preferences and priorities are targeted. For this purpose, the weighting of the criteria that are the subject of decision-makers' preferences needs to be determined.

When examining the MCDM literature, it is possible to come across many methods for determining weight coefficients. In addition to these methods, in this research, a method is developed to determine the objective weight coefficients of variables based on the logarithmic function, which allows the analysis and modelling of variables in terms of their logarithmic relationships. Therefore, the research focuses on the analysis and modelling potential of logarithmic functions because it is known that logarithmic functions are used in different fields and are effective in solving various problems. In this context, the first aim of the research is to present a new method for calculating the weight coefficients of criteria according to decision alternatives within the scope of MCDM. The second aim is to popularize the use of logarithmic functions and increase awareness of their potentials, as logarithmic functions play an important role in solving and analyzing complex problems.

Objective weighting methods and logarithmic functions are explained in the literature of the research. The method section describes the analysis of the proposed method with the dataset. In the conclusion section, the findings of the proposed method are evaluated, and a comparison is made with other objective weight determination techniques.

2. Literature

The selection of decision alternatives is a fundamental part of many decision-making processes. However, when choosing among different alternatives, situations arise where each alternative performs differently on different criteria. Therefore, it is important to accurately determine the weights of criteria in order to compare the performance of decision alternatives and select the most suitable one (Saaty, 2008). This is because traditionally, in multi-criteria decision-making problems, the importance of criteria is determined using weight coefficients (Ecer, 2020).

In the literature of Multi-Criteria Decision Making (MCDM), methods for determining weight coefficients are generally divided into subjective and objective approaches. This distinction is based on the sources of information used in determining the weight coefficients and the subjective or objective nature of the decision process (Ecer, 2020).

The fundamental characteristic of subjective weight coefficients is that they are based on decision-makers' experiences and evaluations made through their personal opinions. Therefore, since decision-makers create values based on their subjective thoughts, these values vary among individuals (Baş, 2021). These weight coefficients are usually obtained based on expert opinions. However, subjective evaluations by experts can lead to errors and biases in the decision process. On the other hand, objective approaches do not consider decision-makers' inconsistencies and uncertainties. Naturally, using mathematical models based on the information in the decision matrix, the weights of criteria can be calculated. In other words, objective weighting methods take into account the structure of the available data in the evaluation process (Ecer, 2020).

When examining the literature on Multi-Criteria Decision Making (MCDM), one can come across several objective weighting methods. These methods can be referred to as ENTROPY, CRITIC, CILOS, IDOCRIW, SD, SVP, MEREC, and LOPCOW. The ENTROPY method is based on the concept of ENTROPY. In this sense, the more disorder a criterion has, the more distinct it will be from others and become the most important criterion. Therefore, the ENTROPY method can be effectively used in the decision-making process. After preparing the decision matrix in this method, the standard values of the decision matrix and the ENTROPY measurement of the criteria are used to determine the ENTROPY weights of the criteria (Ayçin, 2019).

On the other hand, the CRITIC method is based on the relationships between criteria. By analyzing the relationships between criteria, contradictions among them can be identified. Subsequently, the contradictions associated with the criteria are weighted using standard deviation, enabling the determination of the weight coefficient values of the criteria. In the method, first, a decision matrix is created. Then, the normalized values of the decision matrix are calculated. By analyzing the relationships between criteria based on the normalized values, the weights of the criteria can be measured (Diakoulaki et al., 1995).

In the CILOS method, the relative importance of criteria is based on the extent of the impact deviation of other criteria from their ideal maximum and minimum values. Accordingly, if a criterion has a lower impact deviation, its weight coefficient increases. The method involves calculating the decision matrix, normalization, square matrix, and weight system matrix values in sequence, followed by solving a system of linear equations to determine the weight coefficients of the criteria (Zavadskas and Podvezko, 2016).

The IDOCRIW method is composed of the combination of the ENTROPY and CILOS methods. The method is based on determining the relative impact of a missing index. Initially, the weight coefficients of the criteria are determined based on the ENTROPY and CILOS methods using the values of the decision matrix. Then, the ENTROPY and CILOS weights are merged to obtain the IDOCRIW weights (Ecer, 2020).

The LOPCOW method relies on aggregating data from different dimensions to obtain appropriate or ideal weights. Additionally, this method aims to minimize the gaps between the most important and least important criteria. Furthermore, LOPCOW considers the interrelationships between criteria. In this method, the decision matrix is first prepared, and then the values of the decision matrix are normalized. Subsequently, the average square value as a percentage of the standard deviation of the criterion is calculated to eliminate the difference (gap) caused by the size of the data, and the weight coefficients of the criteria are measured (Ecer and Pamucar, 2022).

In the MEREC method, similar to other weighting methods, the decision matrix and the normalized decision matrix are first obtained. Then, the total performance values of the decision alternatives are calculated based on a natural logarithm-based structure. Subsequently, considering each decision alternative's value, the changes in the performance values of the other decision alternatives are determined again based on natural logarithm. At the end of the method, the weight values of the criteria are determined based on the calculation of the subtraction effect on the criterion (sum of absolute deviations). Additionally, in the method, as the influence of criteria on decision alternatives increases, the weight coefficients of the criteria also increase (Keshavarz-Ghorabaee et al., 2021).

The SD method is based on the distance of criteria values from the arithmetic mean of the criteria. In this method, first, the normalization of the decision matrix is achieved based on the decision matrix values. Then, the standard deviation values for each criterion are determined to determine the weights of the criteria (Uludağ and Doğan, 2021). In the SVP method, the weights of the criteria are measured by calculating the variances of the criteria based on the decision matrix values (Demir et al., 2021).

The SECA method allows for the determination of both the performance of decision alternatives and the weight coefficients of criteria relative to decision alternatives. In this method, the decision matrix values are standardized, and subsequently, disagreement degrees and standardization values are calculated using standard deviation. Based on this, the weights of the criteria can be calculated by solving a multi-objective linear model through the optimization of the model (Keshavarz-Ghorabaee et al., 2018).

The DEMATEL method is a subjective weight determination method based on the relationship between criteria. For this purpose, the effects of criteria on each other are determined based on subjective evaluations, where 0 represents no effect, 1 represents low effect, 2 represents moderate effect, 3 represents high effect, and 4 represents very high effect. This information is used to create a direct relationship matrix. Subsequently, the standard relationship matrix, total relationship matrix, relationship diagram, threshold value, and finally, the weight coefficients of the criteria are determined (Gobus and Fontela, 1972). Altıntaş (2021) emphasized that instead of subjective evaluations in the direct relationship matrix, the effects of criteria on each other can be determined using the Somers' d correlation coefficient, allowing for the objective calculation of the weight coefficients of the criteria.

In the MCDA literature, the objective weights of criteria reveal two fundamental characteristics. The first one can be defined as the intensity of contrast in performance of decision alternatives on each criterion or the difference between maximum and minimum values among criteria. The second one is the distinctiveness or conflict among criteria. By revealing and utilizing these two characteristics, which are stored as inherent information in the data defining the multi-criteria problem, decision-makers can benefit in the decision-making process (Ecer, 2020).

In addition to these, another characteristic can be attributed to the potential of criteria to influence each other based on quantitative outcomes. If one criterion has a low-level positive influence on another criterion, activities can be developed concerning the influencing criterion for the improvement of the influenced criterion. Conversely, if the positive influence of one criterion on another leads to a decrease in the development of the influenced criterion, initiatives can be established to reduce or minimize the influence of the influencing criterion on the influenced criterion. Therefore, based on this logic, strategies, policies, and recommendations for the development of criteria can be provided concerning the interrelationships among criteria belonging to any concept. In this regard, logarithmic functions can be used for measuring the weight coefficients of criteria. Because based on logarithmic functions, the values of criteria influencing each other can be determined as dependent and independent variables (Karagöz, 2017).

Logarithmic functions were introduced by John Napier in the late 16th century. Furthermore, logarithmic functions played a crucial role in accurately calculating the orbits and motions of planets. Logarithm, in mathematical terms, represents a power that needs to be raised to a base to obtain a given number, as it is an exponentiation in reverse (Önalan, 2010). For a given $b \in R^+$ and$b \neq R^+$, the logarithmic function($f(x) = log_b x$), denoted as$f(x) = b^x$, is the inverse of the exponential function$f: R \to R^+$, that is one-to-one and onto, where the base b is used. The domain of the function consists of positive real numbers, and the range consists of the set of real numbers (Kartal et al., 2014; Balaban, 2015; Kuruüzüm and Çetin, 2015; Eroğlu, 2017; Barnett et al., 2015).

Logarithmic functions offer several benefits in capturing the interactions between variables. Firstly, logarithmic functions are useful for transforming and smoothing data sets. Particularly in cases where data varies widely across a range, applying logarithmic transformation can make the data more homogeneous and amenable to analysis or normalization (Cleveland, 1994; Johnson and Wichern, 2007; Tabachnick and Fidell, 2013). Secondly, logarithmic scaling emphasizes proportional magnitudes. When the y-axis of a graph is scaled logarithmically, it enhances the visibility of proportional magnitudes (Tufte, 2001). Thirdly, logarithmic functions simplify certain mathematical operations. Specifically, multiplication and division operations can be transformed into addition and subtraction through logarithmic conversion, simplifying calculations in certain scenarios (Kutner, 2004).

In the literature, numerous studies can be found on the applications of logarithmic functions. Olefir and Lastovsky (2021) analyzed mathematical methods for forecasting under market conditions using logarithmic functions. Guo et al. (2020) utilized logarithmic functions to maximize the weighted sum rate (WSR) for all users by jointly designing the beamforming and phase vector of RIS elements. Verma et al. (2020) employed logarithmic functions to identify consumer food waste in an internationally comparable manner, based on food supply, energy deficiency, and consumer welfare. Zeng et al. (2021) proposed a weighted induced logarithmic distance-based method to address multi-attribute decision-making (MADM) problems using q-ROFS information. Choi et al. (2019) used logarithmic functions to model the bounding boxes (bbox) of YOLOv3, one of the most representative one-stage detectors, with Gaussian parameters and redesigned the loss function to improve detection accuracy while supporting real-time operation.

3. Method

3.1. Data Set and Analysis of the Study

The data set of the study consists of the LPI (Logistics Performance Index) component data for 18 countries in the G20 group for the year 2023. In the study, the proposed method was used to calculate the weight coefficients of the LPI components. For convenience, the abbreviations of the LPI components are shown in Table 1.

Table 1. LPI Components and Component Abbreviations

LPI Components	Component Abbreviations
Customs	LPI1
Infrastructure	LPI2
International Shipments	LPI3
Logistics Competence and Quality	LPI4
Timeliness Score	LPI5
Tracking and Tracing	LPI6

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3.2. Proposed Method: Logarithmic Effect Based Measurement (LEBM)

The relationship between two variables can be explained using various modeling approaches and functions. These functions can include linear, quadratic, compound, growth, logarithmic, cubic, S-shaped, exponential, inverse, power, and logistic functions. Depending on the roles of the variables as dependent and independent variables, their relationships can be represented by equations using the SPSS program (Karagöz, 2020).

In the proposed method, the relationships between the criteria are established based on logarithmic functions. Logarithmic functions are effective tools in data transformation and smoothing. Particularly, in cases where data vary widely, logarithmic transformation can make the data more homogeneous and enable analysis without losing information (Johnson and Wichern, 2007). Therefore, within the scope of the LEBM method, logarithmic functions are utilized to examine the relationships between two variables.

When the logarithmic function between two variables is determined using the SPSS program, the extent to which the independent variable's variation, between its maximum and minimum values in the dataset, affects the dependent variable can be calculated through definite integration. This calculation reveals the overall change induced by the independent variable on the dependent variable or the extent of its influence.

$f'(x)$ Is called the antiderivative or indefinite integral of the function$f(x)$. Since$f'(x) = {df(x)}/{dx}$, it can be written as$f'(x)dx = df(x)$. This expression is represented using the infinite and continuous summation symbol$\int$, as$\int f'(x)dx = \int df(x)$. From this equation, the equation $\int f'(x)dx = f(x)$ can be obtained. Therefore, the function to be integrated is$f'(x)$. Furthermore, $\int f(x)dx = F(x) + C$ where $\int_a^b f(x)dx = F(b) - F(a)$ represents the definite integral. Here, "a" represents the lower limit of the integral, and "b" represents the upper limit (Kartal, 2014). Thus, after determining the logarithmic relationships between the criteria using the logarithm function $(y = kx + t * \log(x))$, the extent to which the variation of the independent variable x between the limits "a" and "b" affects or changes the dependent variable "y" can be measured using definite integration. Based on this, the implementation steps of the proposed method are explained below.

Step 1: Obtaining the Decision Matrix

i: 1, 2, 3...n, where n represents the number of decision alternatives

j: 1, 2, 3,...m, where m represents the number of criteria

D: Decision matrix

C: Criterion

d_{ij}: The decision matrix is constructed according to Equation 1, where "i_j" represents the i-th decision alternative on the j-th criterion.

$$D = \left[d_{ij}\right]_{nxm} = \begin{bmatrix} C_1 & C_2 & \dots & C_m \\ x_{11} & x_{12} & & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \quad (1)$$

Step 2: Generation of Logarithmic Functions

Based on the number of criteria, m, logarithmic functions $(y = kx + t * \log(x))$ are generated for the variables up to a quantity of $\left\{2.C(m,2) = 2.\frac{m!}{2!.(m-2)!}\right\}$ using SPSS assistance (CURVE ESTIMATION), considering the logarithmic relationship between them.

$$(1)\ f(C_1) = C_2, f(C_1) = C_3, \dots \dots\ f(C_1) = C_m \quad (2)$$

$$(2)\ f(C_2) = C_1, f(C_2) = C_3, \dots \dots\ f(C_2) = C_m \quad (3)$$

$$(3)\ f(C_3) = C_1, f(C_3) = C_2, \dots \dots\ f(C_3) = C_m \quad (4)$$

$$\vdots \quad \vdots \quad \vdots$$

$$(m)\ f(C_m) = C_1, f(C_m) = C_2, \dots \dots\ f(C_m) = C_{m-1} \quad (5)$$

Third Step: Calculation of Logarithmic Impact Value between Criteria

In this step, the extent to which an independent variable (one criterion) influences or changes a dependent variable (another criterion) is determined by evaluating the independent variable's effect within the range of its maximum and minimum values using definite integral calculation. Here, k represents the logarithmic impact value of one criterion on the other. It is important to ensure the absolute value of the impact values after the integral calculation.

$$(1)\ f(C_1) = C_2\,, \int_{C_{1min.}}^{C_{1maks.}} (f'(C_1))\,dx = \left|k_{C_1 \to C_2}\right| \quad (6)$$

$$(2)\ f(C_1) = C_3\,, \int_{C_{1min.}}^{C_{1maks.}} (f'(C_1))\,dx = \left|k_{C_1 \to C_3}\right| \quad (7)$$

$$(3)\ f(C_1) = C_4\,, \int_{C_{1min.}}^{C_{1maks.}} (f'(C_1))\,dx = \left|k_{C_1 \to C_4}\right| \quad (8)$$

$$\vdots \quad \vdots \quad \vdots$$

$$\left(\frac{m!}{(m-2)!}\right) f(C_m) = C_{m-1}\,, \int_{C_{mmin.}}^{C_{mmaks.}} (f'(C_m))\,dx = \left|k_{C_m \to C_{m-1}}\right| \quad (9)$$

The absolute value of the impact value of one criterion on another criterion is emphasized above. This is because in this method, what matters is not the direction of the influence between criteria, but rather the magnitude of the influence.

Fourth Step: Calculation of the Total Logarithmic Impact Values of Each Criterion (T_c)

In this step, the logarithmic impact values of a criterion on other criteria are summed to measure the overall logarithmic impact value of a criterion on the other criteria.

$$(1)\ for\ C_1\ \left|k_{C_1\to C_2}\right| + \left|k_{C_1\to C_3}\right| + \left|k_{C_1\to C_4}\right| \dots\dots + \left|k_{C_1\to C_m}\right| = \sum_{j=1}^{m-1} \left|k_{C_1\to C_{j+1}}\right| = T_{C_1} \tag{10}$$

$$(2)\ for\ C_2 için\ \left|k_{C_2\to C_1}\right| + \left|k_{C_2\to C_3}\right| + \left|k_{C_2\to C_4}\right| \dots\dots + \left|k_{C_2\to C_m}\right| = \left(\sum_{j=2}^{m-1} \left|k_{C_2\to C_{j+1}}\right|\right) - \left|k_{C_1\to C_2}\right| = T_{C_2} \tag{11}$$

$$(3)\ for\ C_3\ \left|k_{C_3\to C_1}\right| + \left|k_{C_3\to C_2}\right| + \left|k_{C_3\to C_4}\right| \dots\dots + \left|k_{C_3\to C_m}\right| = \left(\sum_{j=3}^{m-1} \left|k_{C_3\to C_{j+1}}\right|\right) - \left|k_{C_3\to C_1}\right| - \left|k_{C_3\to C_2}\right| = T_{C_3} \tag{12}$$

$$\vdots\ \vdots\ \vdots \qquad \vdots\ \vdots\ \vdots \qquad \vdots\ \vdots\ \vdots$$

$$(m)\ for\ C_m\ \left|k_{C_m\to C_1}\right| + \left|k_{C_m\to C_2}\right| + \left|k_{C_m\to C_3}\right| \dots\dots + \left|k_{C_m\to C_{m-1}}\right| = \left(\sum_{j=1}^{m-1} \left|k_{C_m\to C_j}\right|\right) - \left|k_{C_1\to C_m}\right| - \left|k_{C_2\to C_m}\right| - \dots . - \left|k_{C_{m-1}\to C_m}\right| = T_{C_m} \tag{13}$$

Fifth Step: Determination of Criterion Weight Values (w_j)

In this step, the total logarithmic impact value of each criterion on the other criteria is divided by the sum of the total logarithmic impact values of all criteria. This allows for the calculation of the weight coefficient of each criterion.

$$w_j = \frac{T_{C_j}}{\sum_{j=1}^{m} T_{C_j}} \tag{14}$$

The advantages of the LEBM method can be classified into two categories: quantity and quality. These advantages are explained below in bullet points:

Quantity-Based Advantages of the LEBM Method:

One of the key features of the method is that it does not require data normalization or standardization. In the second step, by using logarithmic functions, the data is already normalized, allowing for more homogeneous representation of data with wide-ranging variations. This enhances the analyzability of the data. The impact values between criteria in the second and third steps of the method are within the range of [-1, 0, 1] for each criterion. Additionally, when the data set is normalized, there is a difference between the impact values derived from the logarithmic functions between the criteria before and after normalization. Consequently, the impact values between the criteria, calculated using logarithmic functions based on the data set after normalization, diminish. As a result, when data normalization is performed, the logarithmic impact values between the criteria, determined based on the logarithmic functions, suffer from data loss.

Another significant advantage of the method is its flexible nature, which allows for easy reflection of complex interactions and transformations among the criteria.

The third advantage of the method is that logarithmic transformations reduce the influence of large values in the data set while making small values more pronounced. This process creates a more symmetrical distribution of the data set, thus establishing a more suitable structure for analysis and modeling.

The fourth advantage of the method is that it prevents variables with large values from dominating variables with small values. This enables a fair evaluation among variables in decision-making processes.

The fifth advantage of the method, the method reduces the impact of outliers and enhances the reliability of the analysis results.

Lastly, one of the important features of the method is that it focuses on determining the extent of the influence between criteria, rather than the direction of influence. This allows for a comprehensive understanding of the quantitative impact of criteria on each other.

Qualitative-Based Advantages of the LEBM Method:

Identification of Improvement Opportunities: Criteria with higher weights exert a greater influence on other criteria, making them suitable targets for identifying improvement opportunities. Understanding the relationships between criteria and determining their impact values indicate where improvement efforts should be concentrated. In other words, it allows for investigating the theoretical cause-and-effect relationships between criteria and determining the direction of their influence. Consequently, it becomes easier to identify which criteria should be prioritized or improved based on the decision alternatives.

Prioritization: Determining the weights allows for prioritization among the criteria. Criteria with higher weights are considered more important compared to other criteria. This enables the identification of which criteria should receive greater focus in strategic planning and decision-making processes.

Performance Evaluation: The weight coefficients can be utilized in the performance evaluation of the criteria. Criteria with higher weights are regarded as having a greater impact on the organization's or system's performance. This facilitates more effective performance evaluation and improvement efforts by concentrating on the most critical criteria.

Strategic Planning: The weight coefficients contribute to the appropriate allocation of resources and efforts in the strategic planning process. By focusing on criteria with higher weights, more suitable strategies and actions can be identified to align with strategic objectives. This aids in the development of strategic plans aimed at enhancing the overall performance of the organization or system.

The LEBM method has both advantages and disadvantages. One of the disadvantages is that, compared to many objective weighting methods in the literature, this method requires complex calculations for determining the weight coefficients of the criteria. Particularly as the number of criteria increases, the calculations can become more complicated due to the multitude of interaction values between criteria. Another disadvantage is the reliance on SPSS or other statistical software programs for identifying the logarithmic relationships between criteria. Without the SPSS program, the calculation of weight coefficients according to the method becomes more complex and time-consuming. A third disadvantage is that if there is no theoretical cause-and-effect relationship between the criteria, there may be limited opportunities for improving the criteria. Lastly, the fourth disadvantage is the need for transformation using Z-scores when values in the decision matrix are negative or 0 to ensure that the values are positive and different from zero. This disadvantage is also present in the ENTROPY and MEREC methods, as both methods rely on logarithmic measurements.

The LEBM method shares some similarities with the MEREC method in terms of the applied mathematical approaches. Firstly, both methods consider logarithmic effects. Another similarity is the identification of criteria with significant logarithmic effects as the most important criteria. The differences between the two methods are evident in their computational logic and equations. In the MEREC method, the logarithmic effects of criteria on decision alternatives are taken into account, rather than the effects of criteria on each other. In the LEBM method, on the other hand, the logarithmic effects of criteria on each other are evaluated. Additionally, in the MEREC method, the values of all criteria are taken into account when determining their effects on decision alternatives. In the LEBM method, however, only the logarithmic relationships between two criteria are determined.

4. The Case Study (Conclusion)

The application involved the utilization of the six component values that constitute the 2023 LPI for the 18 countries in the G20 group. These respective component values are represented by equation 1 and are presented in Table 2.

Table 2. Decision Matrix (LPI Component Values of Countries)

Economies	LPI1	LPI2	LPI3	LPI4	LPI5	LPI6
Argentina	2,7	2,8	2,7	2,7	3,1	2,9
Australia	3,7	4,1	3,1	3,9	3,6	4,1
Canada	4,0	4,3	3,6	4,2	4,1	4,1
China	3,3	4,0	3,6	3,8	3,7	3,8
France	3,7	3,8	3,7	3,8	4,1	4,0
Germany	3,9	4,3	3,7	4,2	4,1	4,2

India	3,0	3,2	3,5	3,5	3,6	3,4
Indonesia	2,8	2,9	3,0	2,9	3,3	3,0
Italy	3,4	3,8	3,4	3,8	3,9	3,9
Japan	3,9	4,2	3,3	4,1	4,0	4,0
Korea, Rep.	3,9	4,1	3,4	3,8	3,8	3,8
Mexico	2,5	2,8	2,8	3,0	3,5	3,1
Russia Fed.	2,4	2,7	2,3	2,6	2,9	2,5
Saudi Arabia	3,0	3,6	3,3	3,3	3,6	3,5
South Africa	3,3	3,6	3,6	3,8	3,8	3,8
Türkiye	3,0	3,4	3,4	3,5	3,6	3,5
United King.	3,5	3,7	3,5	3,7	3,7	4,0
USA	3,7	3,9	3,4	3,9	3,8	4,2

In the second step of the model, considering the presence of 6 components, the functional equation denoted by $\left\{2.C(m,2)=2.\frac{m!}{2!.(m-2)!}\right\}$ is used to illustrate the logarithmic relationships among the components, resulting in Equation 2. Therefore, in order to capture the interplay among the components, 30 logarithmic function equations (Equations 2, 3, 4, and 5) were established based on CURVE analysis using SPSS. These respective functions are indicated in Table 3.

Table 3. Logarithmic Functions Derived Based on the Interrelationships between Components

Independent Components	Dependent Components	Logarithmic Functions	Independent Components	Dependent Components	Logarithmic Functions
	LPI2	y=-0,201 + 3,22 * log(x)		LPI1	y=-0,739 + 3,202* log(x)
	LPI3	y=1,151+ 1,805 * log(x)		LPI2	y=-0,777 + 3,474 * log(x)
LPI1→	LPI4	y=0,151 + 2,892 * log(x)	LPI4→	LPI3	y=0,482+ 2,221 * log(x)
	LPI5	y=1,544 + 1,797 * log(x)		LPI5	y=1,018+ 2,100 * log(x)
	LPI6	y=0,191 + 2,918 * log(x)		LPI6	y=-0,498 + 3,280 * log(x)
	LPI1	y=-0,630 + 3,093 * log(x)		LPI1	y=-2,692 + 4,628 * log(x)
	LPI3	y=0,902 + 1,875 * log(x)		LPI2	y=-2,714 + 4,880 * log(x)
LPI2→	LPI4	y=-0,259 + 3,011 * log(x)	LPI5→	LPI3	y=-1,358 + 3,583 * log(x)
	LPI5	y=1,348 + 1,826* log(x)		LPI4	y=2,715 + 4,851 * log(x)
	LPI6	y=0,160+ 2,991 * log(x)		LPI6	y=-2,579 + 4,802 * log(x)
	LPI1	y=0,193 + 2,961 * log(x)		LPI1	y=-0,740 + 3,154 * log(x)
	LPI2	y=-0,176+ 3,205 * log(x)		LPI2	y=-0,711 + 3,368 * log(x)
LPI3→	LPI4	y=-0,308 + 3,284 * log(x)	LPI6→	LPI3	y=0,476 + 2,191 * log(x)
	LPI5	y=0,937+ 2,312 * log(x)		LPI4	y=-0,539 + 3,204* log(x)
	LPI6	y=-0,266 + 3,309* log(x)		LPI5	y=1,050 + 2,042 * log(x)

In the third stage of the method, logarithmic impact values between criteria were calculated using equations 6, 7, 8, and 9. The calculations of the impact values of LPI1 criterion on other criteria are explained below. The measurement of impact values for other LPI components is shown in Appendix A.

- *f(LPI1)=LPI2*

$f(x) = y = -0{,}201 \ + \ 3{,}22\, log(x)$

$f'(x) = 161.log(e)/(50x)$

$$\int_{2.4}^{4} \frac{161log(\boldsymbol{e})}{50x}dx = log(\boldsymbol{e})\left(\frac{161ln(2)}{25} - \frac{161ln(2.4)}{50}\right) = 0{,}714$$

- *f(LPI1)=LPI3*

$f(x) = y = 1.151 + \ 1.805\, log(x)$

$$f'(x) = \frac{361log(\boldsymbol{e})}{200x}$$

$$\int_{2.4}^{4} \frac{361log(\boldsymbol{e})}{200x} dx = log(\boldsymbol{e}) \left(\frac{361ln(2)}{100} - \frac{361ln(2.4)}{200} \right) = 0{,}400$$

- *f(LPI1)=LPI4*

$$f(x) = y = 0.151 + 2.892\, log(x)$$

$$f'(x) = \frac{723log(\boldsymbol{e})}{250x} = 0{,}642$$

$$\int_{2.4}^{4} \frac{723log(\boldsymbol{e})}{250x} dx = log(\boldsymbol{e}) \left(\frac{723ln(2)}{125} - \frac{723ln(2.4)}{250} \right) = 0{,}642$$

- *f(LPI1)=LPI5*

$$f(x) = y = 1.544 + 1.797\, log(x)$$

$$f'(x) = \frac{1797log(\boldsymbol{e})}{1000x}$$

$$\int_{2.4}^{4} \frac{1797log(\boldsymbol{e})}{1000x} dx = log(\boldsymbol{e}) \left(\frac{1797ln(2)}{500} - \frac{1797ln(2.4)}{1000} \right) = 0{,}399$$

- *f(LPI1)=LPI6*

$$f(x) = y = 0.191 + 2.918\, log(x)$$

$$f'(x) = \frac{1459log(\boldsymbol{e})}{500x}$$

$$\int_{2.4}^{4} \frac{1459log(\boldsymbol{e})}{500x} dx = log(\boldsymbol{e}) \left(\frac{1459ln(2)}{250} - \frac{1459ln(2.4)}{500} \right) = 0{,}647$$

In the fourth step of the method, the total logarithmic impact values of each criterion were calculated using equations 10, 11, 12, and 13, and they are presented in Table 3.

Table 3. Sum of Logarithmic Impact Values of LPI Components on Each Other

Independent Component	Dependent Components	Effect Value	Absolute Value	Independent Component	Dependent Components	Effect Value	Absolute Value
LPI1→	LPI2	0,714	0,714	LPI4→	LPI1	0,667	0,667
	LPI3	0,400	0,400		LPI2	0,724	0,724
	LPI4	0,642	0,642		LPI3	0,463	0,463
	LPI5	0,399	0,399		LPI5	0,437	0,437
	LPI6	0,647	0,647		LPI6	0,683	0,683
		Total	2,802			Total	2,974
LPI2→	LPI1	0,625	0,625	LPI5→	LPI1	0,696	0,696
	LPI3	0,379	0,379		LPI2	0,734	0,734
	LPI4	0,609	0,609		LPI3	0,539	0,539
	LPI5	0,369	0,369		LPI4	0,730	0,730
	LPI6	0,604	0,604		LPI6	0,722	0,722
		Total	2,586			Total	3,421
LPI3→	LPI1	0,611	0,611	LPI6→	LPI1	0,711	0,711

LPI2	0,662	0,662	LPI2	0,759	0,759
LPI4	0,678	0,678	LPI3	0,494	0,494
LPI5	0,477	0,477	LPI4	0,722	0,722
LPI6	0,683	0,683	LPI5	0,469	0,469
	Total	3,111		Total	3,155

Furthermore, in Equation 14, the weight coefficients (degrees of importance) of the criteria are calculated, and the values are presented in Table 4.

Table 4. Weighting Coefficients of the Components.

LPI Components	Total Effects	w	Ranking
LPI1	2,802	0,155244	5
LPI2	2,586	0,143277	6
LPI3	3,111	0,172314	3
LPI4	2,974	0,164774	4
LPI5	3,421	0,189540	1
LPI6	3,155	0,174802	2
Total	18,04	------	------

Upon examining Table 4, the weighting coefficients of the LPI components are ranked as follows LPI5, LPI6, LPI3, LPI4, LPI1, and LPI2.

In the study, sensitivity analysis of the LEBM method was conducted in terms of methodology. Sensitivity analysis in the context of MCDA can be performed by comparing the values and rankings obtained by applying different criteria weighting methods to the same data (Gigovič, 2016). Accordingly, for the sensitivity analysis, the weighting coefficients of the LPI components were measured and ranked based on commonly used objective weighting methods in the literature, such as ENTROPY, CRITIC, SD (Standard Deviation), SVP (Statistical Variance Procedure), MEREC, and LOPCOW. The corresponding values are presented in Table 5.

Table 5. Values for Other Methods of Calculating Objective Weighting Coefficients

LPI	ENTROPY		CRITIC		SD	
	Value	Ranking	Value	Ranking	Value	Ranking
LPI1	0,222945	1	0,148589	3	0,196204	1
LPI2	0,210584	2	0,122964	4	0,190162	2
LPI3	0,128961	5	0,319406	1	0,147672	5
LPI4	0,181127	3	0,082131	6	0,175726	3
LPI5	0,076881	6	0,218173	2	0,115892	6
LPI6	0,179502	4	0,108738	5	0,174343	4
LPI	SVP		LOPCOW		MEREC	
	Value	Ranking	Value	Ranking	Value	Ranking
LPI1	0,200716	2	0,154187	5	0,149797	5
LPI2	0,22458	1	0,141623	6	0,132971	6
LPI3	0,111106	5	0,193551	1	0,179704	3
LPI4	0,187108	4	0,158815	4	0,151747	4
LPI5	0,084873	6	0,166201	3	0,188583	2
LPI6	0,191619	3	0,185623	2	0,197197	1

When Tables 4 and 5 are examined together, it is observed that the ranking of the LPI criterion weighting coefficients determined according to the LEBM method differs from the LPI criterion rankings generated by other methods. Furthermore, according to Table 5, the ranking of LPI criterion weighting coefficient values measured using the LEBM method is consistent with the ranking of decision alternatives as 1 for SVP, 4 for LOPCOW, and 5 for MEREC. In the context of sensitivity analysis, a visual representation of the differentiation distances between the weighting coefficient values of LPI components calculated according to the LEBM method and other criterion weighting determination methods, based on the values specified in Table 5, was created. The corresponding visual is presented in Figure 1.

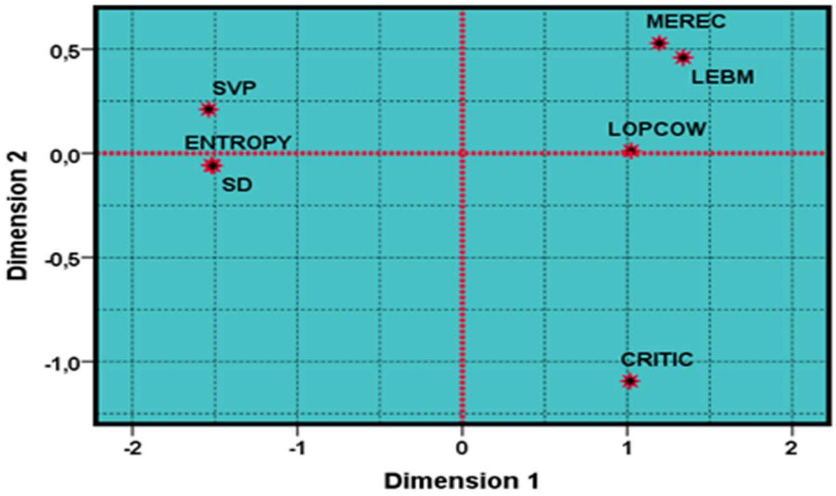

Figure 1. Discrimination Distance Visualization Based on Methods

Upon examining Figure 1, it is observed that the LEBM method has different positions in the space compared to other methods. Additionally, according to Figure 1, it is determined that the LEBM method is closest to the LOPCOW and MEREC methods. In relation to this, the correlation values between the weighting coefficient values of the LPI components calculated within the scope of the methods are presented in Table 6.

Table 6. Correlation Values between Weighting Coefficient Values of Identified LPI Components based on Methods

Methods	LEBM	ENTROPY	CRITIC	SD	SVP	LOPCOW	MEREC
LEBM	1						
ENTROPY	-0,879**	1					
CRITIC	0,423	-0,635**	1				
SD	-0,876**	0,999**	-0,628**	1			
SVP	-0,848**	0,959**	-0,781**	0,957**	1		
LOPCOW	0,652**	-0,493*	0,575*	-0,465*	-0,555*	1	
MEREC	0,889**	-0,678**	0,393	-0,669*	-0,652*	0,838**	1

p*<.05, p<.01**

When Table 6 is examined, it is observed that the relationships between the weighting coefficient values of LPI components measured within the LEBM ENTROPY, SD, and SVP methods are significant, negative, and high. In contrast, it is observed that the weighting coefficients of LPI criteria calculated according to the LEBM method have a positive, insignificant, and weak relationship with the weighting coefficients of LPI criteria measured using the CRITIC method, a positive, significant, and moderate relationship with the weighting coefficients of LPI criteria measured using the LOPCOW method, and a positive, significant, and high-level relationship with the weighting coefficients of LPI criteria measured using the MEREC method.

In addition to that, 10 scenarios were created by assigning different quantities to the LPI values of countries, and the degrees of importance of LPI criteria were measured according to the methods within the scope of these scenarios. Upon examining the scenarios, it was found that none of the weighting coefficients of the criteria determined by the ENTROPY, CRITIC, SD, and SVP methods were consistent with the ranking of the weighting coefficient values of LPI components calculated using the LEBM method. Within the LOBCOW method, the ranking of 4 criteria in 7 scenarios and 3 criteria in 3 scenarios, and within the MEREC method, the ranking of 5 criteria in all 10 scenarios, showed consistency with the ranking of LPI criterion weighting coefficient values measured using the LEBM method. Furthermore, it has been determined that the correlation values among the weighting coefficient values of LPI criteria determined according to the methods in the created scenarios are generally consistent with the correlation values shown in Table 6.

5. Results and Discussion

Multi-criteria decision making is a widely used method for solving complex decision problems. This method aims to make choices among different alternatives by considering a set of criteria. However, the importance of each criterion may vary, and therefore, it is important to weight the criteria. Determining the weights allows for an objective and unbiased approach in the decision-making process, clarifying the relationships and priorities among the criteria. This enables more consistent and reliable results to be obtained in the decision-making process. Consequently, many researchers have developed new methods for calculating the weight coefficients of criteria. Each method has contributed to the literature of Multiple Criteria Decision Making (MCDM) by employing different techniques. Furthermore, as new techniques for determining the weight coefficients of criteria continue to emerge, there is an increasing specialization in calculating these weights. Therefore, in this study, a new method based on logarithmic functions (Logarithmic ENTROPY-Based Method or LEBM) is proposed for calculating the weight coefficients of criteria.

The underlying logic of the LEBM method is to establish logarithmic effects among the criteria. Considering the advantages of logarithmic functions and the proposed method (flattening the data structure, equalizing differences in magnitudes, reducing the impact of outliers in the dataset, linearizing relationships), the effects among the criteria can be calculated, and the criterion with the highest cumulative effect can be evaluated as the most important criterion. The most important criterion has the potential to influence other criteria, thus activities or measures related to the most important criterion can contribute to the development of other criteria. Additionally, a system can be developed to determine the strategies for decision alternatives in relation to the most important criterion(s).

The dataset of the study consisted of the Logistics Performance Index (LPI) data of 18 countries in the G20 group for the year 2023. First, the weight coefficients of the LPI components measured by the LEBM method were calculated. Second, the weight coefficients of the LPI components measured by the LEBM method were compared with the weight coefficients of the LPI criteria measured by other objective weighting methods (ENTROPY, CRITIC, Standard Deviation, Statistical Variance Procedure, MEREC, and LOPCOW) within the scope of sensitivity analysis using the same dataset. According to the findings, the weight coefficient rankings of the LPI criteria determined according to the LEBM method were observed to be different from the weight coefficient rankings of the LPI components measured by the ENTROPY, CRITIC, Standard Deviation, Statistical Variance Procedure, MEREC, and LOPCOW methods. The ranking of the weight coefficients of the LPI components determined by the LEBM method was consistent with the ranking of the weight coefficients of the LPI components determined by the MEREC method to the highest extent. In the continuation of the sensitivity analysis, a discrimination distance visualization of the weight coefficients of the LPI components determined according to the methods was created. According to the findings, it was determined that the LEBM method was closest to the MEREC and LOPCOW methods in the space.

Furthermore, the correlation values between the weight coefficients of the LPI criteria measured by the LEBM method and the weight coefficients of the criteria measured by other weighting methods were calculated. According to the findings, significant relationships were found between the weight coefficients of the LPI criteria determined within the scope of the LEBM method and the weight coefficients of the LPI components measured by the ENTROPY, CRITIC, Standard Deviation, Statistical Variance Procedure, LOPCOW, and MEREC methods. In this context, it was determined that the weight coefficients of the LPI components determined within the scope of the LEBM method were negatively and highly correlated with the LPI components calculated by the ENTROPY, Standard Deviation, and Statistical Variance Procedure methods. Furthermore, positive and moderate-to-high relationships were observed between the weight coefficients of the LPI components determined by the LEBM method and the weight coefficients of the LPI components determined by the CRITIC, LOPCOW, and MEREC methods, respectively, except for the CRITIC method. However, it was found that the relationship between the weight coefficients of the LPI determined by the LEBM method and the weight coefficients of the LPI determined by the CRITIC method was insignificant.

In addition, different quantities were assigned to the LPI values of countries within the framework of 10 scenarios. In each scenario, the ranking of the LPI criteria determined by the proposed method showed the highest consistency with the rankings determined by the MEREC method. Furthermore, it was determined that the importance degrees of the LPI components determined by the methods within the scenarios, where different values were assigned to the LPI criteria, were very similar to the relationship quantity values calculated by the methods based on the original LPI values.

In conclusion, this analysis attempts to demonstrate that the weights of criteria can be measured using the LEBM method within the framework of MCDM literature. The proposed method is considered to provide a valuable tool for the objective evaluation of the performance of decision alternatives. The research findings can serve as an important reference for researchers and decision-makers in the relevant field. Consequently, it is evaluated that the research results will encourage a greater focus on logarithmic functions in mathematical modeling processes in academic circles, businesses, and other organizations. Additionally, it is concluded that the LEBM method is an effective tool for decision-makers in the selection and decision-making processes regarding the performance of decision alternatives.

Conflict of interest

No conflict of interest was declared by the authors.

Appendix A

LPI2

- *f(LPI2)=LPI1*

$$\text{deriv}(-0.63+3.093\log(x),x) = \frac{3093\log(\boldsymbol{e})}{1000x}$$

$$\int_{2.7}^{4.3} \frac{3093\log(\boldsymbol{e})}{1000x}\,dx = \log(\boldsymbol{e})\left(\frac{3093\ln(4.3) - 3093\ln(2.7)}{1000}\right) = 0{,}625$$

- *f(LPI2)=LPI3*

$$\text{deriv}(0.902+1.875\log(x),x) = \frac{15\log(\boldsymbol{e})}{8x}$$

$$\int_{2.7}^{4.3} \frac{15\log(\boldsymbol{e})}{8x}\,dx = \log(\boldsymbol{e})\left(\frac{15\ln(4.3) - 15\ln(2.7)}{8}\right) = 0{,}379$$

- *f(LPI2)=LPI4*

$$\text{deriv}(0.259+3.011\log(x),x) = \frac{3011\log(\boldsymbol{e})}{1000x}$$

$$\int_{2.7}^{4.3} \frac{3011\log(\boldsymbol{e})}{1000x}\,dx = \log(\boldsymbol{e})\left(\frac{3011\ln(4.3) - 3011\ln(2.7)}{1000}\right) = 0{,}609$$

- *f(LPI2)=LPI5*

$$\text{deriv}(1.348+1.826\log(x),x) = \frac{913\log(\boldsymbol{e})}{500x}$$

$$\int_{2.7}^{4.3} \frac{913\log(\boldsymbol{e})}{500x}\,dx = \log(\boldsymbol{e})\left(\frac{913\ln(4.3) - 913\ln(2.7)}{500}\right) = 0{,}369$$

- *f(LPI2)=LPI5*

$$\text{deriv}(0.1601+2.991\log(x),x) = \frac{2991\log(\boldsymbol{e})}{1000x}$$

$$\int_{2.7}^{4.3} \frac{2991\log(\boldsymbol{e})}{1000x}\,dx = \log(\boldsymbol{e})\left(\frac{2991\ln(4.3) - 2991\ln(2.7)}{1000}\right) = 0{,}604$$

LPI3

- *f(LPI3)=LPI1*

$$\text{deriv}(0.193+2.961\log(x),x) = \frac{2961\log(\boldsymbol{e})}{1000x}$$

$$\int_{2.3}^{3.7} \frac{2961\log(\boldsymbol{e})}{1000x}\,dx = \log(\boldsymbol{e})\left(\frac{2961\ln(3.7) - 2961\ln(2.3)}{1000}\right) = 0{,}611$$

- *f(LPI3)=LPI2*

$$\mathrm{deriv}(-0.176{+}3.205\log(x),x) = \frac{641\log(\boldsymbol{e})}{200x}$$

$$\int_{2.3}^{3.7} \frac{641\log(\boldsymbol{e})}{200x}\,dx = \log(\boldsymbol{e})\left(\frac{641\ln(3.7) - 641\ln(2.3)}{200}\right) = 0{,}662$$

- *f(LPI3)=LPI4*

$$\mathrm{deriv}(-0.308{+}3.284\log(x),x) = \frac{821\log(\boldsymbol{e})}{250x}$$

$$\int_{2.3}^{3.7} \frac{821\log(\boldsymbol{e})}{250x}\,dx = \log(\boldsymbol{e})\left(\frac{821\ln(3.7) - 821\ln(2.3)}{250}\right) = 0{,}678$$

- *f(LPI3)=LPI5*

$$\mathrm{deriv}(0.937{+}2.312\log(x),x) = \frac{289\log(\boldsymbol{e})}{125x}$$

$$\int_{2.3}^{3.7} \frac{289\log(\boldsymbol{e})}{125x}\,dx = \log(\boldsymbol{e})\left(\frac{289\ln(3.7) - 289\ln(2.3)}{125}\right) = 0{,}477$$

$$\mathrm{deriv}(-0.266{+}3.309\log(x),x) = \frac{3309\log(\boldsymbol{e})}{1000x}$$

$$\int_{2.3}^{3.7} \frac{3309\log(\boldsymbol{e})}{1000x}\,dx = \log(\boldsymbol{e})\left(\frac{3309\ln(3.7) - 3309\ln(2.3)}{1000}\right) = 0{,}683$$

LPI4

- *f(LPI4)=LPI1*

$$\mathrm{deriv}(-0.739{+}3.202\log(x),x) = \frac{1601\log(\boldsymbol{e})}{500x}$$

$$\int_{2.6}^{4.2} \frac{1601\log(\boldsymbol{e})}{500x}\,dx = \log(\boldsymbol{e})\left(\frac{1601\ln(4.2) - 1601\ln(2.6)}{500}\right) = 0{,}667$$

- *f(LPI4)=LPI2*

$$\mathrm{deriv}(-0.777{+}3.474\log(x),x) = \frac{1737\log(\boldsymbol{e})}{500x}$$

$$\int_{2.6}^{4.2} \frac{1737\log(\boldsymbol{e})}{500x}\,dx = \log(\boldsymbol{e})\left(\frac{1737\ln(4.2) - 1737\ln(2.6)}{500}\right) = 0{,}724$$

- *f(LPI4)=LPI3*

$$\mathrm{deriv}(0.482{+}2.221\log(x),x) = \frac{2221\log(\boldsymbol{e})}{1000x}$$

$$\int_{2.6}^{4.2} \frac{2221\log(\boldsymbol{e})}{1000x}\,dx = \log(\boldsymbol{e})\left(\frac{2221\ln(4.2) - 2221\ln(2.6)}{1000}\right) = 0{,}463$$

- *f(LPI4)=LPI5*

$$\text{deriv}(1.018{+}2.1\log(x){,}x) = \frac{21\log(\boldsymbol{e})}{10x}$$

$$\int_{2.6}^{4.2} \frac{21\log(\boldsymbol{e})}{10x}\,dx = \log(\boldsymbol{e})\left(\frac{21\ln(4.2) - 21\ln(2.6)}{10}\right) = 0{,}437$$

• *f(LPI4)=LPI6*

$$\text{deriv}(-0.498{+}3.28\log(x){,}x) = \frac{82\log(\boldsymbol{e})}{25x}$$

$$\int_{2.6}^{4.2} \frac{82\log(\boldsymbol{e})}{25x}\,dx = \log(\boldsymbol{e})\left(\frac{82\ln(4.2) - 82\ln(2.6)}{25}\right) = 0{,}683$$

LPI5

• *f(LPI5)=LPI1*

$$\text{deriv}(-2.692{+}4.628\log(x){,}x) = \frac{1157\log(\boldsymbol{e})}{250x}$$

$$\int_{2.9}^{4.1} \frac{1157\log(\boldsymbol{e})}{250x}\,dx = \log(\boldsymbol{e})\left(\frac{1157\ln(4.1) - 1157\ln(2.9)}{250}\right) = 0{,}696$$

• *f(LPI5)=LPI2*

$$\text{deriv}(-2.714{+}4.88\log(x){,}x) = \frac{122\log(\boldsymbol{e})}{25x}$$

$$\int_{2.9}^{4.1} \frac{122\log(\boldsymbol{e})}{25x}\,dx = \log(\boldsymbol{e})\left(\frac{122\ln(4.1) - 122\ln(2.9)}{25}\right) = 0{,}734$$

• *f(LPI5)=LPI3*

$$\text{deriv}(-1.358{+}3.583\log(x){,}x) = \frac{3583\log(\boldsymbol{e})}{1000x}$$

$$\int_{2.9}^{4.1} \frac{3583\log(\boldsymbol{e})}{1000x}\,dx = \log(\boldsymbol{e})\left(\frac{3583\ln(4.1) - 3583\ln(2.9)}{1000}\right) = 0{,}539$$

• *f(LPI5)=LPI4*

$$\text{deriv}(2.715{+}4.851\log(x){,}x) = \frac{4851\log(\boldsymbol{e})}{1000x}$$

$$\int_{2.9}^{4.1} \frac{4851\log(\boldsymbol{e})}{1000x}\,dx = \log(\boldsymbol{e})\left(\frac{4851\ln(4.1) - 4851\ln(2.9)}{1000}\right) = 0{,}730$$

• *f(LPI5)=LPI6*

$$\text{deriv}(-2.579{+}4.802\log(x){,}x) = \frac{2401\log(\boldsymbol{e})}{500x}$$

$$\int_{2.9}^{4.1} \frac{2401\log(\boldsymbol{e})}{500x}\,dx = \log(\boldsymbol{e})\left(\frac{2401\ln(4.1) - 2401\ln(2.9)}{500}\right) = 0{,}722$$

LPI6

• *f(LPI6)=LPI1*

$$\text{deriv}(-0.74{+}3.154\log(x){,}x) = \frac{1577\log(\boldsymbol{e})}{500x}$$

$$\int_{2.5}^{4.2} \frac{1577\log(\boldsymbol{e})}{500x}\,dx = \log(\boldsymbol{e})\left(\frac{1577\ln(4.2) - 1577\ln(2.5)}{500}\right) = 0{,}711$$

• *f(LPI6)=LPI2*

$$\text{deriv}(-0.711{+}3.368\log(x),x) = \frac{421\log(\boldsymbol{e})}{125x}$$

$$\int_{2.5}^{4.2} \frac{421\log(\boldsymbol{e})}{125x}\,dx = \log(\boldsymbol{e})\left(\frac{421\ln(4.2) - 421\ln(2.5)}{125}\right) = 0{,}759$$

• *f(LPI6)=LPI3*

$$\text{deriv}(0.476{+}2.191\log(x),x) = \frac{2191\log(\boldsymbol{e})}{1000x}$$

$$\int_{2.5}^{4.2} \frac{2191\log(\boldsymbol{e})}{1000x}\,dx = \log(\boldsymbol{e})\left(\frac{2191\ln(4.2) - 2191\ln(2.5)}{1000}\right) = 0{,}494$$

• *f(LPI6)=LPI4*

$$\text{deriv}(-0.539{+}3.204\log(x),x) = \frac{801\log(\boldsymbol{e})}{250x}$$

$$\int_{2.5}^{4.2} \frac{801\log(\boldsymbol{e})}{250x}\,dx = \log(\boldsymbol{e})\left(\frac{801\ln(4.2) - 801\ln(2.5)}{250}\right) = 0{,}722$$

• *f(LPI6)=LPI5*

$$\text{deriv}(1.05{+}2.042\log(x),x) = \frac{1021\log(\boldsymbol{e})}{500x}$$

$$\int_{2.5}^{4.2} \frac{1021\log(\boldsymbol{e})}{500x}\,dx = \log(\boldsymbol{e})\left(\frac{1021\ln(4.2) - 1021\ln(2.5)}{500}\right) = 0{,}469$$

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