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Evaluation of University Professors Using the Spherical Fuzzy AHP and Grey MARCOS Multi-Criteria Decision-Making Model: A Case Study

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ABSTRACT

This study introduces a hybrid multi-criteria decision-making (MCDM) model combining Spherical Fuzzy AHP and Grey MARCOS methods to evaluate university professors comprehensively. Addressing the limitations of traditional assessment methods, the model incorporates subjective and imprecise data while maintaining transparency and precision. Seven criteria, including teaching quality, accessibility to students, professional competence, preparation and organization, student feedback, contribution to the university, and ethical behavior, were used. Spherical Fuzzy AHP was employed to determine the weight coefficients of the criteria, leveraging fuzzy logic to capture uncertainties. Subsequently, Grey MARCOS ranked professors by evaluating their performance against ideal and anti-ideal solutions using interval grey numbers. The hybrid approach effectively mitigates bias and provides an accurate ranking of alternatives, even under conditions of incomplete or subjective data. The results validate the model's robustness and adaptability, highlighting its utility for both individual evaluations and broader institutional improvements. This methodology offers actionable insights for enhancing teaching quality, encouraging professional growth, and strengthening institutional competitiveness. The findings emphasize the importance of integrating advanced MCDM techniques to ensure comprehensive and equitable assessments in academia. This study provides a practical framework for universities aiming to elevate educational standards while addressing global challenges in higher education evaluation. By applying this hybrid model, institutions can foster a culture of continuous improvement and achieve more reliable and impactful outcomes in professor evaluations.

1. Introduction

The teaching profession is a dynamic practice that evolves and adapts daily. Therefore, it is crucial to establish an evaluation system that enables a detailed review of the needs for improving the skills

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and competencies of professors, providing the basis for continuous improvement and transformation of their work by the results obtained.

To evaluate the work of university professors, it is essential to clearly define their competency profile. Torelló [1] highlights three key aspects of professional activity: the micro-context, which includes activities in classrooms, seminars, and laboratories; the general context, encompassing the socio-professional and cultural environment; and the institutional context, which pertains to work within the department, faculty, and university. These aspects significantly contribute to establishing criteria for evaluating university professors.

Considering the attitudes of students in educational faculties toward the evaluation of professors is required, as their impressions directly reflect the quality of their mentors' work.

Professors involved in the education of future teachers not only impart professional knowledge in a particular field but also shape the professional profile associated with that discipline.

Allowing students to participate in the evaluation of professors creates opportunities for critical reflection on pedagogical practices and helps identify areas for improvement. Often, professors despite being top experts in their disciplines—lack formal training in effective teaching methods, which evaluation can highlight and address for improvement [2].

Different approaches indicate that the definition of the profile of university professors has a significant impact on the methods of their evaluation. This profile is formed in accordance with activities that are essential to their teaching work, such as lesson planning, implementing classroom strategies, professional behavior and values, as well as interaction and collaboration with colleagues and students.

Evaluation of professors is a key process in improving the quality of higher education, as it enables the identification of strengths and weaknesses in their work. Traditional assessment methods often rely on students' subjective grades, which can lead to imprecise and biased results [3]. At the same time, the growing expectations from universities, in terms of the quality of teaching and contribution to research, require reliable and transparent evaluation methods. In the modern context, the multidimensionality of the professor's professional work further complicates the evaluation process, as it includes various aspects such as expertise, pedagogical skills and ethical behavior [4]. The use of multi-criteria decision-making methods in combination with fuzzy logic and a set of grey numbers allows for the quantification of subjective assessments and the reduction of the influence of extreme opinions. These methods provide more accurate results through the evaluation of defined criteria. The evaluation of professors not only provides feedback for their professional development but also contributes to strengthening the competitiveness of educational institutions. The introduction of advanced methods, such as Spherical Fuzzy AHP and Grey MARCOS, addresses the complexity of this problem and enhances decision-making processes. These methods help achieve a balance between the qualitative and quantitative aspects of evaluation. This topic is highly relevant to researchers in the field of education and to universities aiming to improve overall institutional performance.

Existing methods of evaluating professors are usually based on student surveys [5], peer-review analyses, or statistical data on their research work. Although student surveys provide direct insight into perceptions of teaching quality, they are often subject to subjectivity and bias, as they can reflect students' personal preferences rather than the actual quality of instruction [6]. Peer-review evaluations, while more professional, are often time-consuming and can be fraught with professional rivalries or collegial sympathies. Statistical data, such as the number of published papers or citations, serve as important indicators of scientific activity but neglect pedagogical skills and contributions to teaching. While combining these methods can offer a more comprehensive perspective, their integration often proves complex and unreliable. One of the key drawbacks of traditional methods is the lack of systematization in the analysis of multiple criteria and considering their interrelationships.

Moreover, most methods lack the flexibility to adapt to the diverse contexts and specifics of individual educational institutions. The limitations are further reflected in the inability to quantify subjective assessments in a way that reduces the extremes. The introduction of multi-criteria decision-making methods, such as AHP, DIBR, EDAS, MARCOS, MAIRCA, MABAC, WASPAS, and BWM solves these problems to some extent but still does not address uncertainties and ambiguities in the data. Therefore, the application of fuzzy logic in combination with multi-criteria methods is vital for improving the evaluation process and achieving more accurate results.

The integration of Spherical Fuzzy AHP and Grey MARCOS methods represents a significant advancement in multi-criteria decision-making. Spherical Fuzzy AHP extends the traditional AHP by incorporating spherical fuzzy sets, allowing for a more nuanced expression of uncertainty and imprecision in pairwise comparisons. This makes it particularly effective in scenarios where expert judgments are vague or subjective.

The Grey MARCOS method complements this approach by addressing situations with incomplete or partially known data, using grey numbers to evaluate alternatives relative to ideal and anti-ideal solutions. Together, these methods create a robust framework capable of handling both uncertainty and ambiguity.

The combined application enhances decision accuracy by integrating the strengths of both methodologies, making it a reliable solution for complex decision-making problems. It is particularly useful in fields like education, healthcare, and urban planning, where criteria are diverse and interdependent. By introducing these methods, decision-makers can derive rankings that better reflect real-world complexities, providing more reliable outcomes. Their adaptability to various domains and decision contexts underscores their potential as dependable tools in academic and professional settings.

The significance of this topic is evident in the ongoing evaluation and ranking of universities, which are conducted in various ways and based on diverse evaluation criteria [7]. The goal of evaluating professors is to systematically and objectively assess the quality of their work through various aspects, including teaching, research, interaction with students, and adherence to the code of ethics. The application of the grey number model allows accurate rankings even in situations where the available data is subjective or unclear. Fuzzy logic provides a tool for quantifying uncertainty and uncertainty in assessment, which contributes to a more realistic representation of professor performance. In this model, the Spherical Fuzzy AHP method is used to determine the weighting coefficients of the criteria, allowing for a more precise definition of their significance. The grey MARCOS method is used to rank professors, which links alternatives with ideal and anti-ideal solutions, providing clear and transparent results [8]. The evaluation is based on a multi-criteria approach that encompasses key aspects of the professor's professional work, such as expertise, engagement and contribution to the institution. The aim is to identify and reward the best professors, thereby encouraging their professional development and enhancing the quality of their work.

This method provides a universally applicable solution that can be adapted to the specific needs of educational institutions. In the long term, the results of the evaluation are used to plan professional development, strengthen the competitiveness of universities and improve the quality of education and research. In this way, evaluation becomes a key mechanism for improving the entire education system.

The evaluation of professors is crucial for ensuring the quality of the educational process, as it allows for an accurate analysis of their professional performance. Through the evaluation process, key strengths and weaknesses are identified, which provide guidelines for improving the teaching work and personal development of professors. In this way, evaluation contributes to the improvement of teaching methods, better student outcomes and reinforcing the reputation of the educational institution. It also provides transparency in the education system, allowing students, colleagues and management to see the quality of teachers' work. One of the key objectives is to identify areas where additional investment in training, resources or mentoring is needed to achieve a higher level of quality. Quality assurance through evaluation contributes to the harmonization of educational institutions with modern standards and expectations of the global labor market. Evaluation of professors by students largely provides reliable information [9], but an evaluation scheme is very important to mostly avoid subjectivity.

The use of fuzzy methods in the evaluation of professors brings significant precision and reliability, even in situations where the available data are unclear or partially subjective. Thanks to these methods, the results are generated thoroughly and transparently, allowing an objective evaluation of key aspects, such as teaching, research and professional contribution. The results obtained not only serve as a basis for rewarding excellence but also as an incentive for professors to continuously improve the quality of teaching and research work. In addition, the evaluation contributes to the identification of areas that require improvement, allowing strategic planning of professional development.

In the long run, this approach enhances the overall quality of the education system. By fostering innovation and accountability, it contributes to the creation of a more competitive academic environment that is focused on the needs of students and society. On a broader societal level, improving the quality of education through such evaluations directly affects the formation of competent experts, ready to respond to the complex challenges of the future.

The use of fuzzy methods, such as Spherical Fuzzy AHP for defining weighting coefficients and grey MARCOS for ranking professors, provides a universally applicable evaluation model. Such a model can be tailored to the specific needs of each educational institution, while at the same time improving trust in the evaluation process and strengthening its importance in the educational and social community.

Table 1 presents a comprehensive literature analysis highlighting the application of AHP, Spherical Fuzzy AHP, Fuzzy AHP, MARCOS, and Grey MARCOS methods.

2. Methodology

The Spherical Fuzzy AHP and Grey MARCOS methods bring substantial benefits to domains requiring multi-criteria decision-making. Their combination provides a robust framework for handling complex problems characterized by uncertainty and incomplete information. Spherical Fuzzy AHP enables precise modelling of subjective expert opinions by utilizing spherical fuzzy sets, which capture uncertainty more effectively than traditional methods. This makes it particularly suitable for fields such as education, healthcare, and urban planning, where decisions involve diverse and interdependent criteria.

Grey MARCOS complements this by addressing incomplete data through grey numbers, making it ideal for scenarios where full information is unavailable. Together, these methods enhance ranking accuracy by bridging the gap between precise and imprecise data. They improve decision consistency by ensuring logical and coherent judgments in pairwise comparisons. Furthermore, their adaptability supports dynamic environments, enabling their application in evaluating performance, resource optimization, and sustainable development.

Table 1
Literature analysis

Research Subject and Reference	Applied Methods
Contractor assessment during the project life cycle [10]	Spherical fuzzy AHP, AHP, Grey AHP, Fuzzy AHP
Bloodmobile location selection for resilient blood supply chain [11]	Spherical fuzzy AHP - COPRAS
Applied to solve the problem of evaluating and selecting an outsourced manufacturer [12]	Spherical fuzzy AHP - WASPAS
Evaluating the condition of saltwater pipes in Hong Kong [13]	Spherical fuzzy AHP – MARCOS
An Approach for the Evaluation of E-Service Quality in the Airline Industry [14]	Fuzzy AHP – Fuzzy MARCOS
Advanced manufacturing system selection [15]	Spherical fuzzy AHP-TOPSIS
Tech-center location selection [16]	Spherical fuzzy AHP - MULTIMOORA
Digital transformation strategy analysis in the airline industry [17]	SWOT – fuzzy AHP – fuzzy MARCOS
Enhanced FMEA Methodology for Evaluating Mobile Learning Platforms [18]	GRA – fuzzy AHP
Analysis of Non-Kinetic Gun Selection [19]	DIBR II-Grey MARCOS
Evaluation of Hazardous Solid Waste Treatment and Disposal Technologies [20]	AHP - MARCOS
Selecting gears and cutting fluids [21]	AHP - MARCOS
Landfill location selection for healthcare waste in urban areas [22]	BWM – grey MARCOS
Identification and Evaluation of Human-Induced Threats to Urban Areas [23]	Grey BWM- Grey MARCOS
Selecting Suppliers for a Steel Manufacturing Company [24]	Grey MARCOS
Selection of a dump truck [25]	Fuzzy LMAW – grey MARCOS

The combination of Spherical Fuzzy AHP and Grey MARCOS also facilitates group decision-making, aggregating expert opinions to derive a consensus effectively. Their integration into existing frameworks is straightforward, offering practical usability and broad applicability. These methods stand out as reliable tools for modern decision-making challenges, providing transparent and accurate solutions across various domains.

The application of the Spherical Fuzzy AHP – grey MARCOS hybrid model (Figure 1) for the selection of the best professor at a higher education institution to increase the quality of teaching, was realized by determining the weight of the criteria using the SF – AHP method, and the ranking of professors using the grey MARCOS method.

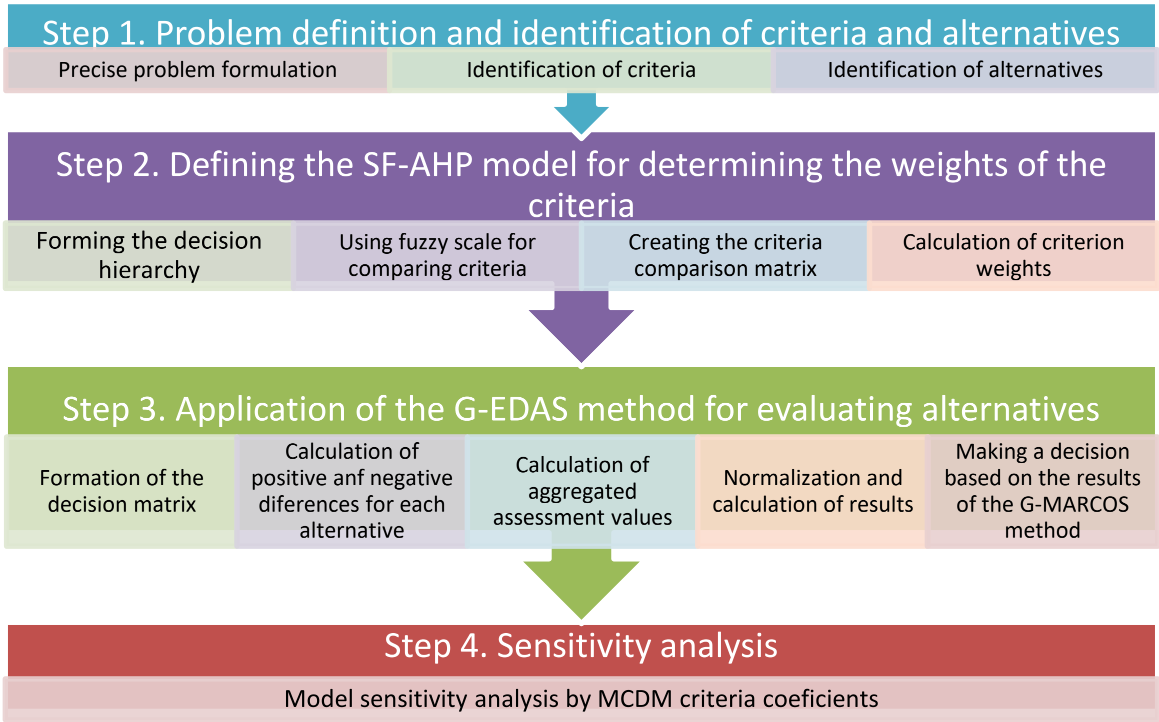

Fig. 1. Spherical Fuzzy AHP – Grey MARCOS model

2.1 Spherical Fuzzy AHP method

Pairwise comparison algorithms typically rely on precise real numbers. However, expert evaluations in such comparisons are often subjective and imprecise. As a result, integrating fuzzy approaches into the AHP method offers a practical solution for managing the inherent uncertainty in expert assessments [26].

Incorporating a fuzzy formulation for pairwise comparisons, the proposed fuzzy-AHP model retains the same phases as the standard AHP model. The steps of the AHP model are as follows [27]:

i. Define the problem by creating a model that represents the key aspects and relationships of the issue [28].
ii. Compare items in pairs, providing judgments based on knowledge or opinion.
iii. Quantify the judgments using appropriate numerical values.
iv. Use these values to determine the priorities of the components in the hierarchy.

The fuzzy triangular membership function can be represented mathematically as follows:

$$\lambda(x)=\begin{cases}0, \ x<1, \\ \frac{x-1}{m-1}, \ l\leq x\leq m, \\ \frac{u-x}{u-m}, \ m\leq x\leq u, \\ 0, \ x>u.\end{cases} \quad (1)$$

2.2 Spherical fuzzy sets

Spherical fuzzy sets [29-37] have been used in many papers where they have proven to be a very reliable tool that assists decision-makers. It is feasible to design spherical fuzzy sets (SFS) (Figure 2) based on the decision-maker's hesitation, independent of the membership λ and non-membership ω degrees provided the following conditions are satisfied:

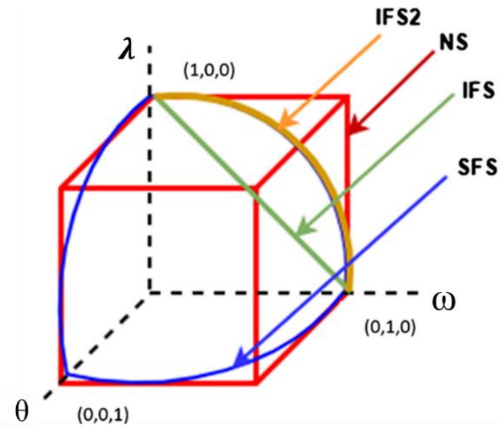

Fig. 2. IFS, PFS, NS, and SFS geometric illustrations [38]

$$0 \le \lambda_A^2(u) + \omega_A^2(u) + \theta_A^2(u) \le 1 \forall u \in U \quad (2)$$

On the sphere surface. Eq. (2) will be

$$\lambda_A^2(u) + \omega_A^2(u) + \theta_A^2(u) = 1 \forall u \in U \quad (3)$$

SFS offers decision-makers the ability to extend various forms of fuzzy sets [39]. A spherical fuzzy set ÃS in the universe U is defined as:

$$\widetilde{A_s} = \{\langle u, (\lambda_{\widetilde{A_s}}(u), \omega_{\widetilde{A_s}}(u), \theta_{\widetilde{A_s}}(u)) \rangle | u \in U\}, \quad (4)$$

Where:

$\lambda_{\widetilde{A_s}}(u): U \to [0,1]$,

$\omega_{\widetilde{A_s}}(u): U \to [0,1]$,

$\theta_{\widetilde{A_s}}(u): U \to [0,1]$.

For each u corresponding to $\widetilde{A_s}$, he rejection degree is determined using the values of the membership degrees $\lambda_{\widetilde{A_s}}(u)$, non-membership $\omega_{\widetilde{A_s}}(u)$, and hesitancy $\theta_{\widetilde{A_s}}(u)$ as follows [40,41]. Refusal degree is calculated as follows:

$$X_{\widetilde{A_s}}(u) = \sqrt{1 - \lambda_{\widetilde{A_s}}^2(u) - \omega_{\widetilde{A_s}}^2(u) - \theta_{\widetilde{A_s}}^2(u)} \quad (5)$$

2.3 Zadeh's SFS extension principle

Zadeh's Spherical Fuzzy Sets (SFS) extension principle builds upon the classic extension principle in fuzzy set theory to handle higher levels of uncertainty and imprecision. It generalizes traditional fuzzy set operations by introducing spherical membership functions, which account for membership, non-membership, and hesitancy degrees in a normalized way. This extension is particularly useful in multi-criteria decision-making and modeling scenarios where ambiguity is inherent, providing a more nuanced representation of uncertainty.

For $i = 1, \ldots, n, U_i$ be a universe and let $V \neq 0$.

Let $f: X_{i=1}^{n-1} \; U_i \to V$ be a mapping, where $y = f(z_1, \ldots, z_n)$.

Let z_i be a linguistic variable on U_i for $i = 1, \ldots, n$. Assume that i, $\widetilde{A_{S1}}$ is a SFS on U_i and then, the output of mappings f is $\widetilde{B}_s$. For $y \in V$, the set $\widetilde{B}_s$ is SFS on V defined as follows:

$$\widetilde{B}_s(y) = \left\{\max_{Z(y)}\left(\min_{i=1}^{n} \lambda_{\widetilde{A_{S1}}}(u_i)\right), \min_{Z(y)}\left(\max_{i=1}^{n} \omega_{\widetilde{A_{S1}}}(u_i)\right), \min_{Z(y)}\left(\min_{i=1}^{n} \theta_{\widetilde{A_{S1}}}(u_i)\right) \forall u_i \in U_i, i = 1, \ldots \ldots, n\right\}, \quad (6)$$

if $f^{-1}(y) \neq 0$,

Where:

$Z(y) = f^{-1}(y)$.

For operations like addition and multiplication [42]

$$\widetilde{A}_s \oplus \widetilde{B}_s = \left\{z, \left(\max_{Z=x+y} \min\{\lambda_{\widetilde{A}_s}(x), \lambda_{\widetilde{B}_s}(y)\}\right), \left(\min_{Z=x+y} \max\{\omega_{\widetilde{A}_s}(x), \omega_{\widetilde{B}_s}(y)\}\right), \left(\min_{Z=x+y} \min\{\theta_{\widetilde{A}_s}(x), \theta_{\widetilde{B}_s}(y)\}\right), \right. \quad (7)$$

$$\widetilde{A}_s \oplus \widetilde{B}_s = \left\{z, \left(\max_{Z=x+y} \min\{\lambda_{\widetilde{A}_s}(x), \lambda_{\widetilde{B}_s}(y)\}\right), \left(\min_{Z=x+y} \max\{\omega_{\widetilde{A}_s}(x), \omega_{\widetilde{B}_s}(y)\}\right), \left(\min_{Z=x+y} \min\{\theta_{\widetilde{A}_s}(x), \theta_{\widetilde{B}_s}(y)\}\right) \right. \quad (8)$$

The geometric mean of spherical weight for $w = (w_1, w_2, \ldots, w_n)$; $w_i[0,1]; \sum_{i=1}^{n} w_i = 1$, is defined as follows [43]:

$$SWGM_w(\tilde{A}_{S1}^{w_1}, \ldots, \tilde{A}_{Sn}) = \tilde{A}_{S1}^{w_1} + \tilde{A}_{S1}^{w_2} + \cdots + \tilde{A}_{Sn}^{w_n} = \left\{\prod_{i=1}^{n} \lambda_{\tilde{A}_{Si}}^{w_i}, \left[1 - \prod_{i=1}^{n}\left(1 - \omega_{\tilde{A}_{Si}}^2\right)^{w_i}\right]^{1/2}, \left[\prod_{i=1}^{n}(1 - \lambda_{\tilde{A}_{Si}}^2)^{w_i} - \prod_{i=1}^{n}\left(1 - \omega_{\tilde{A}_{Si}}^2 - \theta_{\tilde{A}_{Si}}^2\right)^{w_i}\right]^{1/2}\right\} \quad (9)$$

Table 2 presents the linguistic evaluation scale in SF AHP.

Table 2
Linguistic criteria for evaluating importance in pairwise comparisons

SF $(\lambda, \omega, \theta)$		Score index
(0.9, 0.1, 0.0)	Absolutely more importance (AMI)	9
(0.8, 0.2, 0.1)	Very high importance (VHI)	7
(0.7, 0.3, 0.2)	High importance (HI)	5
(0.6, 0.4, 0.3)	Slightly more importance (SMI)	3
(0.5, 0.4, 0.4)	Equally importance (EI)	1
(0.4, 0.6, 0.3)	Slightly low importance (SLI)	1/3
(0.3, 0.7, 0.2)	Low importance (LI)	1/5
(0.2, 0.8, 0.1)	Very low importance (VLI)	1/7
(0.1, 0.9, 0.0)	Absolutely low importance (ALI)	1/9

The Consistency Ratio (CR) and Consistency Index (CI) for each pairwise comparison matrix in AHP, as defined in the corresponding equations, are calculated to assess consistency, and all matrices have been verified as consistent [44]. In Saaty's Analytic Hierarchy Process (AHP) [45], the symbol λ_{max} represents the largest eigenvalue of a pairwise comparison matrix, while n indicates the matrix's dimension. The Random Index (R.I.), dependent on matrix size, reflects the average Consistency Index (C.I.) derived from numerous randomly generated pairwise comparison matrices, as established by Saaty [46].

$$CI = \frac{\lambda_{max} - n}{n-1}, \; CR = \frac{CI}{RI} \quad (10)$$

2.4 Application of the grey MARCOS method

The MARCOS method, a relatively new MCDM technique, establishes relationships between alternatives and reference values (ideal and anti-ideal solutions) [47] to evaluate their functionality. These relationships enable the method to rank alternatives by comparing them to ideal and unsuitable solutions. The method prioritizes the alternative closest to the ideal point and furthest from the anti-ideal point.

This research applies the MARCOS method with an adaptation based on grey theory, specifically utilizing interval grey numbers, to effectively address uncertainties [48]. Grey theory [49-51], as introduced by Ju-Long [52], provides a framework for managing information that is partially known and partially unknown. It classifies information into three categories, as illustrated in Figure 3, facilitating decision-making under conditions of uncertainty.

The usability functions in the MARCOS method serve to establish preferences, defining an alternative's position relative to ideal and anti-ideal solutions. This structured approach allows for a comprehensive ranking of compromised solutions.

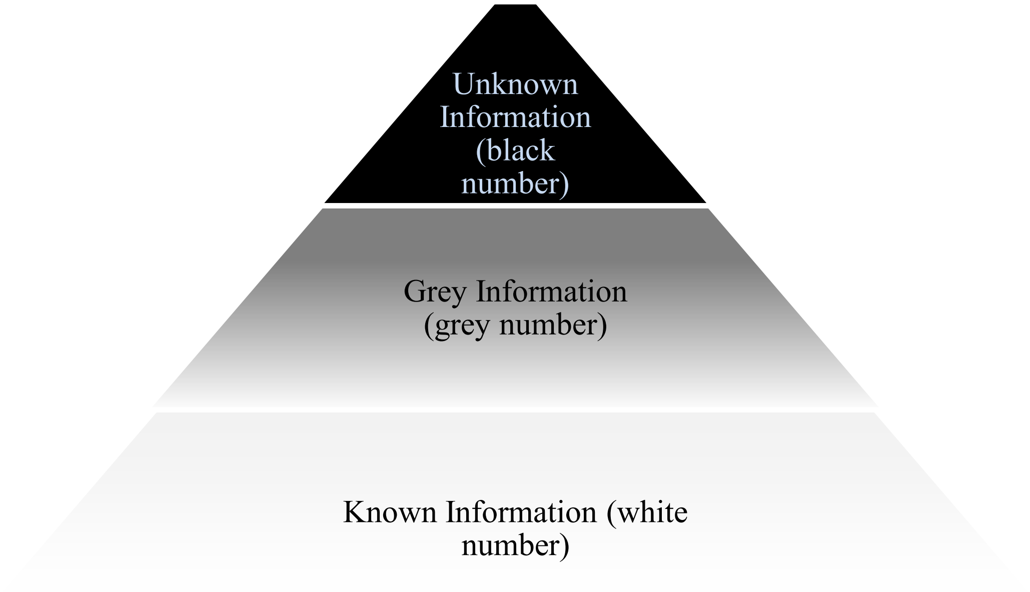

Fig. 3. Grey theory

If set Z is a universal set, then set grey (G) of set Z is defined with two functions: $\bar{\mu}_G(Z)$ and $\underline{\mu}_G(Z)$, where $\bar{\mu}_G(Z): Z \rightarrow [0,1]$ and $\underline{\mu}_G(Z): Z \rightarrow [0,1]$, as well as $\bar{\mu}_G(Z) \geq \underline{\mu}_G(Z), z \in Z$. The interval Grey number (⊗G) is defined as follows: ⊗ G = [$\underline{G}$, $\overline{G}$], where $\underline{G}$ denotes the lower limit of the grey number ⊗ G, and $\overline{G}$ signifies the upper limit, with $\underline{G} > \overline{G}$. When $\underline{G}$ equals $\overline{G}$, the grey number ⊗ G transitions into a white number, indicating a precisely known and determined value. The computational fundamentals of Grey numbers have been widely analyzed and documented in various studies.

The MARCOS method can be applied by following these sequential steps [53,54].

Step 1. The creation of the initial decision-making matrix (L).

First, the experts e = {e_1, e_2, . . ., e_k} evaluate all alternatives by every criterion, by which they obtain Grey initial decision-making matrices for every expert. $L^{(e)} = \left[\otimes\, l_{ij}^{(e)}\right]_{m\times n}$, where $\otimes\, l_{ij}^{(e)} = \left[\underline{l}_{ij}^{(e)}, \bar{l}_{ij}^{(e)}\right]$, 1 ≤ i ≤ m and 1 ≤ j ≤ n. Expression (11) describes the aggregation process used to consolidate the decision-making matrices provided by all experts. This step results in the initial aggregated decision-making matrix, further elaborated in expression (12).

$$\otimes\, l_{ij} = \left[\underline{l}_{ij}, \bar{l}_{ij}\right] = \begin{cases} \underline{l}_{ij} = \left\{\frac{1}{c(c-1)} \sum_{i,j}^{c} \underline{l}_i^p \underline{l}_i^q \right\}^{\frac{1}{p+q}} \\ \bar{l}_{ij} = \left\{\frac{1}{c(c-1)} \sum_{i,j}^{c} \bar{l}_i^p \bar{l}_i^q \right\}^{\frac{1}{p+q}} \end{cases} i \neq j \tag{11}$$

$$L = \left[\otimes\, l_{ij}\right]_{m\times n} = \begin{bmatrix} [\underline{l}_{11}, \bar{l}_{11}] & [\underline{l}_{12}, \bar{l}_{12}] & \cdots & [\underline{l}_{1n}, \bar{l}_{1n}] \\ [\underline{l}_{21}, \bar{l}_{21}] & [\underline{l}_{22}, \bar{l}_{22}] & \cdots & [\underline{l}_{2n}, \bar{l}_{2n}] \\ \vdots & \vdots & \ddots & \vdots \\ [\underline{l}_{m1}, \bar{l}_{m1}] & [\underline{l}_{m2}, \bar{l}_{m2}] & \cdots & [\underline{l}_{mn}, \bar{l}_{mn}] \end{bmatrix}_{m\times n} \tag{12}$$

Step 2. Formulation of an expanded initial matrix involves defining both the ideal (AI) and anti-ideal (AAI) solutions. The ideal solution represents the best possible outcome for each criterion, while the anti-ideal solution corresponds to the worst. This process is mathematically defined using the following equations:

$$\triangle L = \begin{matrix} & K_1 & K_2 & \dots & K_n \\ AAI & \otimes l_{aa1} & \otimes l_{aa2} & \cdots & \otimes l_{aan} \\ A_1 & \otimes l_{11} & \otimes l_{12} & \cdots & \otimes l_{1n} \\ A_2 & \otimes l_{21} & \otimes l_{22} & \cdots & \otimes l_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ A_m & \otimes l_{m1} & \otimes l_{m2} & \cdots & \otimes l_{mn} \\ AI & \otimes l_{ai1} & \otimes l_{ai2} & \cdots & \otimes l_{ain} \end{matrix} \tag{13}$$

$$\mathrm{AI} = \max_{j} \bar{\mathrm{l}}_{\mathrm{ij}} \quad \text{if } \mathrm{j} \in \mathrm{B} \text{ and } \min_{j} \underline{\mathrm{l}}_{\mathrm{ij}} \quad \text{if } \mathrm{j} \in \mathrm{C} \tag{14}$$

$$\mathrm{AAI} = \min_{j} \underline{\mathrm{l}}_{\mathrm{ij}} \quad \text{if } \mathrm{j} \in \mathrm{B} \text{ and } \max_{j} \bar{\mathrm{l}}_{\mathrm{ij}} \quad \text{if } \mathrm{j} \in \mathrm{C} \tag{15}$$

In these equations, B represents the set of benefit criteria, while C represents the set of cost criteria.

Step 3. Normalization of the expanded initial matrix (L).

The normalized matrix $\widetilde{NM}$ is represented as $\left[\widetilde{NM}_{ij}\right]_{m\times n}$, the elements are sequentially determined using expressions (16) and (17), in the specified order

$$\otimes \widetilde{nm}_{ij} = \frac{\otimes l_{ij}}{\max\limits_{1\le i\le m}\{\bar{l}_{ij}\}} = \left(\frac{\underline{l}_{ij}}{\max\limits_{1\le i\le m}\{\bar{l}_{ij}\}}, \frac{\bar{l}_{ij}}{\max\limits_{1\le i\le m}\{\bar{l}_{ij}\}},\right) \; if\ j \in B \tag{16}$$

$$\otimes \tilde{n}m_{ij} = \frac{\min\limits_{1\le i\le m}\{\underline{l}_{ij}\}}{\otimes l_{ij}} = \left(\frac{\min\limits_{1\le i\le m}\{\underline{l}_{ij}\}}{\bar{l}_{ij}}, \frac{\min\limits_{1\le i\le m}\{\underline{l}_{ij}\}}{\underline{l}_{ij}}\right) \; if\ j \in C \tag{17}$$

Step 4. Calculation of the weighted normalization $WN = \left[\otimes wn_{ij}\right]_{m\times n}$

Through the multiplication of the normalized matrix $\widetilde{NM}$ by the weight coefficients assigned to each criterion, the resulting matrix WN is derived.

Step 5. Assessing the usefulness of alternatives involves utilizing expressions (18) and (19) to ascertain the utility degree concerning both the anti-ideal and the ideal solutions.

$$\otimes C_i^+ = \frac{\otimes S_i}{\otimes S_{Ai}}\left[\frac{\underline{S}_i}{\bar{S}_{Ai}}, \frac{\bar{S}_i}{\underline{S}_{Ai}}\right] \tag{18}$$

$$\otimes C_i^- = \frac{\otimes S_i}{\otimes S_{AAi}}\left[\frac{\underline{S}_i}{\bar{S}_{AAi}}, \frac{\bar{S}_i}{\underline{S}_{AAi}}\right] \tag{19}$$

Here:

$$\otimes S_i = \sum_{i=1}^{n} \otimes wn_{ij} = \left(\sum_{i=1}^{n} \underline{wn}_{ij}, \sum_{i=1}^{n} \overline{wn}_{ij}\right) \tag{20}$$

In these equations, S_i(i = 1, 2, ..., m) represents the total sum of the elements within the weighted matrix for both the lower and upper bounds.

Step 6. Define the utility function for the alternatives $\otimes f(C_i)$.

The utility function for the alternatives is calculated using the specified expression (21).

$$f(C_i) = \frac{C_i^+ + C_i^-}{1 + \frac{1-f(C_i^+)}{f(C_i^+)} + \frac{1-f(C_i^-)}{f(C_i^-)}} \tag{21}$$

Where $f(C_i^-)$ the function represents the utility relative to the anti-ideal solution, while $f(C_i^+)$ denotes the utility function relative to the ideal solution. These functions are determined by applying expressions (22) and (23).

$$\otimes f(C_i^+) = \frac{\otimes C_i^-}{\max\limits_{1\le i\le m}\{\otimes C_i^+ + \otimes C_i^-\}} \tag{22}$$

$$\otimes f(C_i^-) = \frac{\otimes C_i^+}{\max\limits_{1\le i\le m}\{\otimes C_i^+ + \otimes C_i^-\}} \tag{23}$$

Given that all values in expression (21) are crisp, it's essential to convert the grey values from expressions (22) and (23) into crisp values using the provided expression (24):

$$g_{\lambda} = (1-\lambda) \times \underline{g} + \lambda \times \overline{g} \quad (24)$$

Where λ represents the whitening coefficient $\lambda \in [0,1]$.

Step 7. Ranking alternatives based on their priority.

The ranking is established by organizing the utility function values $f(C_i)$ in descending order, where higher values indicate a better ranking for the corresponding alternative.

3. Results

In this part of the paper, the criteria are defined, the weight coefficients of the criteria are determined using the Spherical fuzzy AHP method, after which the equations from the defined grey MARCOS method are applied and the results of the applied model are presented.

3.1 Defining the criteria

By analyzing the content and engaging experts, the criteria that will be used in the evaluation of professors at a higher education institution have been defined. The following criteria have been defined: K1 - quality of teaching, K2 - accessibility to students, K3 - professional qualifications, K4 - preparation and organization, K5 - grades by students, K6 - contribution to the university, K7 - ethical behavior.

K1 - The quality of teaching is assessed by the ability of the professor to convey knowledge clearly and comprehensibly to students. Key aspects of this evaluation include the structure of the lecture and the logical flow of ideas. The interactivity of lectures, the involvement of students in discussions and practical examples further improve the quality of teaching. Furthermore, the professor should be able to adjust the complexity of the topic to match the students' level of understanding. The use of modern technologies, visual materials and other pedagogical tools also contributes to this criterion [55]. The relevance of the content to current trends and industry needs is also important. Consistency in presentation and avoidance of ambiguity are key elements of high-grade teaching. Effective time management during lectures ensures that all key concepts are covered. Clear assignment instructions and explanations help students achieve better results. Finally, student feedback is intended as an additional indicator of the success of the teaching process. The criterion is evaluated based on the results obtained by surveying students and is of a beneficial type.

K2 - The availability of professors to students implies their willingness to answer questions and provide support to students outside of regular class hours. This criterion is assessed based on consultations, open appointments for questions and interactions via e-mail or other communication channels. The teacher should respond promptly and accurately, especially when it comes to deadlines for projects or exams. Accessibility also includes the willingness of professors to assist students in solving academic problems or dilemmas. In addition, their ability to create an atmosphere of trust encourages students to seek help freely. Accessibility during final projects and theses is also an important element. A professor who provides additional resources, guides, and advice contributes to better learning. The balance between professional relationships and friendly communication makes it easier to interact. This criterion reflects the general level of commitment of the professor to the needs of his students. In the end, students highly rate professors who show empathy and understanding for their individual challenges.

K3 - Professional competence is assessed based on the depth of the professor's knowledge in their field. Their ability to transmit up-to-date and accurate information based on modern research and trends is evaluated. Publishing scientific papers and participating in conferences are additional indicators of expertise. The professor should demonstrate a broader perspective by connecting theoretical concepts with practical applications. Their experience in the industry, if any, can further enrich the teaching process. It is important that the professor answers complex questions from students with clarity and confidence. The ability to recognize and resolve mistakes in the classroom demonstrates their authority in the subject. Continuous training through seminars, courses or research proves a commitment to professional development. A professor should be able to motivate students through a demonstration of their passion for the field. In addition, their contribution to teamwork and collaboration within the faculty is also important.

K4 - Preparation and organization, well-prepared professors carefully plan their lectures and materials. This criterion includes the organization of the curricula and consistency in their implementation. A well-defined course helps students to better understand what is expected of them. The professor should use a variety of teaching resources, such as presentations, guides, and practical assignments [56]. Adherence to the schedule and time of lectures shows their professionalism. Timely publication of materials and assignments to students is necessary for timely preparation. Organization also includes a clear explanation of the evaluation criteria. Also, adjusting the curriculum when necessary demonstrates the flexibility of the teacher. Consistent improvement of teaching based on feedback contributes to the quality of teaching. Well-organized professors ensure that the learning process runs smoothly.

K5 - Assessment by students, students are key evaluators of the quality of the professor's work, as they are directly involved in the teaching process [57,58]. This criterion encompasses the overall impression that the professor leaves through his teaching, communication and interaction. Students are likely to find the classes valuable, engaging, and inspiring. Their satisfaction often hinges on the professor's ability to effectively motivate and engage them. Student feedback can be quantitative (grades) or qualitative (comments) [59]. A professor who receives positive grades shows a high success rate in the transfer of knowledge. Negative comments can point to areas for improvement, such as clearer presentation or better adaptation to students [60]. Feedback is also used to adapt future lectures and working methods. Respecting the opinions of students creates an atmosphere of mutual respect. Student satisfaction reflects not only their opinion of the professors, but also of the overall quality of the teaching [61]. The paper uses quantitative assessments obtained by students during the self-evaluation of the higher education institution.

K6 - Contribution to the university is measured through the professor's engagement in academic projects, research and development. Their role in mentoring students through final theses and doctoral dissertations is important. A professor who takes on additional responsibilities, such as organizing seminars or leading teams, demonstrates his commitment to the development of the institution. Their participation in the creation of new study programs enriches the education system. An active collaboration with colleagues on projects contributes to better coordination and knowledge sharing. Professors who publish papers in collaboration with the university enhance its reputation. An important aspect of this criterion is the connection of the university with industry and society through practical projects. Participation in committees, commissions, councils, and other university bodies demonstrates their willingness to contribute to the institution's management. Their ability to inspire both colleagues and students contributes to the enrichment of the academic community. This criterion highlights the overall value of the professor to the university.

K7 - Ethical behavior and professionalism of professors are key to creating a positive academic atmosphere. Respect for diversity and inclusiveness in working with students and colleagues are highly valued. A professor should behave responsibly and adhere to academic standards, rules and norms. Transparency in assessment and objectivity in the assessment of students demonstrates integrity. Their willingness to accept constructive criticism contributes to mutual respect. Maintaining confidentiality in working with students reflects a professional relationship. Ethical behavior also includes avoiding any form of discrimination or favoritism. Respect for working hours, resources, and colleagues is a key aspect of professionalism. Teachers should be role models for students through their behavior and attitude. Lastly, consistent ethical behavior contributes to the creation of a positive reputation for the university.

Such detailed assessments ensure accurate ranking of professors, using fuzzy logic to reduce subjectivity and the grey MARCOS method for objective decision-making. Seven criteria were defined that were used for evaluation, and 20 alternatives (professors) for evaluation.

3.1 Determination of weighting coefficients of criteria

The Spherical Fuzzy AHP method of multi-criteria decision-making was used to determine the weighting coefficients of the criteria. By applying equations 1 to 10 and using Table 2, the results shown in Table 3 are obtained.

K1 - the quality of teaching, K2 - accessibility to students, K3 - professional qualifications, K4 - preparation and organization, K5 - grades by students, K6 - contribution to the university, and K7 - ethical behavior.

Table 3
Defining Weight Coefficients for Criteria Using the SF-AHP Method

Criteria	Spherical Fuzzy Weights			Crisp Weights
K_1 – quality of teaching	0.745	0.251	0.214	0.201
K_2 – accessibility to students	0.403	0.612	0.259	0.102
K_3 – professional qualifications	0.644	0.356	0.261	0.170
K_4 -preparation and organization	0.457	0.535	0.294	0.116
K_5 – grade's by students	0.750	0.252	0.201	0.203
K_6 – contribution to the university	0.516	0.488	0.264	0.134
K_7 – ethical behavior	0.309	0.689	0.228	0.076

Consistency Ratio (CR) is 0.0864.

Table 5 defines the initial ranking matrix of professors, which is the initial step in the application of the grey MARCOS method, and grades are obtained by converting linguistic grades into quantitative ones (Table 4).

Table 4
Assessment of linguistic expressions and their corresponding grey values

Performance	Abbreviation	Scale of grey number
Very Good	VG	[0.9, 1.0]
Good	G	[0.6, 0.9]
Medium Good	MG	[0.5, 0.6]
Fair	D	[0.4, 0.5]
Medium Poor	MP	[0.3, 0.4]
Poor	P	[0.1, 0.3]
Very Poor	VP	[0.0, 0.1]

Table 5
Initial decision matrix

	0.201		0.102		0.170		0.116		0.203		0.134		0.076	
	K_1		K_2		K_3		K_4		K_5		K_6		K_7	
P1	0.656	0.825	0.465	0.566	0.794	0.966	0.532	0.693	0.636	0.707	0.532	0.693	0.794	0.966
P2	0.794	0.966	0.532	0.693	0.636	0.707	0.693	0.933	0.424	0.636	0.332	0.432	0.636	0.707
P3	0.497	0.656	0.465	0.566	0.566	0.794	0.424	0.636	0.566	0.794	0.432	0.532	0.636	0.707
P4	0.432	0.532	0.283	0.354	0.465	0.566	0.497	0.656	0.693	0.933	0.424	0.636	0.794	0.966
P5	0.332	0.432	0.283	0.354	0.396	0.497	0.566	0.794	0.354	0.424	0.424	0.636	0.693	0.933
P6	0.354	0.424	0.354	0.424	0.532	0.693	0.532	0.693	0.354	0.424	0.566	0.794	0.636	0.707
P7	0.424	0.636	0.566	0.794	0.693	0.933	0.465	0.566	0.432	0.532	0.656	0.825	0.794	0.966
P8	0.636	0.707	0.532	0.693	0.636	0.707	0.656	0.825	0.794	0.966	0.115	0.265	0.693	0.933
P9	0.566	0.794	0.566	0.794	0.424	0.636	0.566	0.794	0.424	0.636	0.365	0.465	0.693	0.933
P10	0.365	0.465	0.354	0.424	0.432	0.532	0.432	0.532	0.465	0.566	0.000	0.153	0.636	0.707
P11	0.200	0.306	0.465	0.566	0.332	0.432	0.332	0.432	0.354	0.424	0.242	0.370	0.656	0.825
P12	0.058	0.224	0.693	0.933	0.115	0.265	0.200	0.306	0.283	0.354	0.058	0.224	0.636	0.707
P13	0.071	0.212	0.693	0.933	0.200	0.306	0.115	0.265	0.432	0.532	0.200	0.306	0.794	0.966
P14	0.283	0.354	0.636	0.707	0.354	0.424	0.465	0.566	0.465	0.566	0.365	0.465	0.693	0.933
P15	0.354	0.424	0.432	0.532	0.532	0.693	0.532	0.693	0.566	0.794	0.636	0.707	0.424	0.636
P16	0.693	0.933	0.424	0.636	0.794	0.966	0.794	0.966	0.424	0.636	0.636	0.707	0.424	0.636
P17	0.424	0.636	0.532	0.693	0.693	0.933	0.566	0.794	0.566	0.794	0.794	0.966	0.693	0.933
P18	0.465	0.566	0.465	0.566	0.354	0.424	0.566	0.794	0.354	0.424	0.636	0.707	0.636	0.707
P19	0.432	0.532	0.115	0.265	0.465	0.566	0.058	0.224	0.354	0.424	0.566	0.794	0.794	0.966
P20	0.332	0.432	0.000	0.071	0.432	0.532	0.212	0.283	0.465	0.566	0.424	0.636	0.424	0.636

Once the aggregated matrix is constructed, the initial decision-making matrix is expanded by determining the ideal (AI) and anti-ideal (AAI) solutions, as defined by expressions (14) and (15). The expanded initial decision-making matrix (L) is then outlined and presented in Table 6.

Table 6
Extended integrated matrix (L)

	0.201		0.102		0.170		0.116		0.203		0.134		0.076	
	K_1		K_2		K_3		K_4		K_5		K_6		K_7	
AAI	0.058		0.212		0.000		0.071		0.115		0.265		0.058	
P1	0.656	0.825	0.465	0.566	0.794	0.966	0.532	0.693	0.636	0.707	0.532	0.693	0.794	0.966
P2	0.794	0.966	0.532	0.693	0.636	0.707	0.693	0.933	0.424	0.636	0.332	0.432	0.636	0.707
P3	0.497	0.656	0.465	0.566	0.566	0.794	0.424	0.636	0.566	0.794	0.432	0.532	0.636	0.707
P4	0.432	0.532	0.283	0.354	0.465	0.566	0.497	0.656	0.693	0.933	0.424	0.636	0.794	0.966
P5	0.332	0.432	0.283	0.354	0.396	0.497	0.566	0.794	0.354	0.424	0.424	0.636	0.693	0.933
P6	0.354	0.424	0.354	0.424	0.532	0.693	0.532	0.693	0.354	0.424	0.566	0.794	0.636	0.707
P7	0.424	0.636	0.566	0.794	0.693	0.933	0.465	0.566	0.432	0.532	0.656	0.825	0.794	0.966
P8	0.636	0.707	0.532	0.693	0.636	0.707	0.656	0.825	0.794	0.966	0.115	0.265	0.693	0.933
P9	0.566	0.794	0.566	0.794	0.424	0.636	0.566	0.794	0.424	0.636	0.365	0.465	0.693	0.933
P10	0.365	0.465	0.354	0.424	0.432	0.532	0.432	0.532	0.465	0.566	0.000	0.153	0.636	0.707
P11	0.200	0.306	0.465	0.566	0.332	0.432	0.332	0.432	0.354	0.424	0.242	0.370	0.656	0.825
P12	0.058	0.224	0.693	0.933	0.115	0.265	0.200	0.306	0.283	0.354	0.058	0.224	0.636	0.707
P13	0.071	0.212	0.693	0.933	0.200	0.306	0.115	0.265	0.432	0.532	0.200	0.306	0.794	0.966
P14	0.283	0.354	0.636	0.707	0.354	0.424	0.465	0.566	0.465	0.566	0.365	0.465	0.693	0.933
P15	0.354	0.424	0.432	0.532	0.532	0.693	0.532	0.693	0.566	0.794	0.636	0.707	0.424	0.636
P16	0.693	0.933	0.424	0.636	0.794	0.966	0.794	0.966	0.424	0.636	0.636	0.707	0.424	0.636
P17	0.424	0.636	0.532	0.693	0.693	0.933	0.566	0.794	0.566	0.794	0.794	0.966	0.693	0.933
P18	0.465	0.566	0.465	0.566	0.354	0.424	0.566	0.794	0.354	0.424	0.636	0.707	0.636	0.707
P19	0.432	0.532	0.115	0.265	0.465	0.566	0.058	0.224	0.354	0.424	0.566	0.794	0.794	0.966
P20	0.332	0.432	0.000	0.071	0.432	0.532	0.212	0.283	0.465	0.566	0.424	0.636	0.424	0.636
AI	0.794	0.966	0.693	0.933	0.794	0.966	0.794	0.966	0.794	0.966	0.794	0.966	0.794	0.966

The elements of the expanded initial decision-making matrix (L) are normalized using expressions (16) and (17), resulting in the normalized matrix $\widetilde{NM}$ as displayed in Table 7.

Table 7
Normalized matrix $\widetilde{NM}$

	0.201		0.102		0.170		0.116		0.203		0.134		0.076	
	K_1		K_2		K_3		K_4		K_5		K_6		K_7	
AAI	0.060	0.220	0.000	0.076	0.120	0.274	0.060	0.231	0.293	0.366	0.000	0.158	0.439	0.659
P1	0.679	0.854	0.499	0.606	0.822	1.000	0.551	0.717	0.659	0.732	0.551	0.717	0.822	1.000
P2	0.822	1.000	0.571	0.743	0.659	0.732	0.717	0.965	0.439	0.659	0.343	0.447	0.659	0.732
P3	0.514	0.679	0.499	0.606	0.586	0.822	0.439	0.659	0.586	0.822	0.447	0.551	0.659	0.732
P4	0.447	0.551	0.303	0.379	0.482	0.586	0.514	0.679	0.717	0.965	0.439	0.659	0.822	1.000
P5	0.343	0.447	0.303	0.379	0.410	0.514	0.586	0.822	0.366	0.439	0.439	0.659	0.717	0.965
P6	0.366	0.439	0.379	0.455	0.551	0.717	0.551	0.717	0.366	0.439	0.586	0.822	0.659	0.732
P7	0.439	0.659	0.606	0.851	0.717	0.965	0.482	0.586	0.447	0.551	0.679	0.854	0.822	1.000
P8	0.659	0.732	0.571	0.743	0.659	0.732	0.679	0.854	0.822	1.000	0.120	0.274	0.717	0.965
P9	0.586	0.822	0.606	0.851	0.439	0.659	0.586	0.822	0.439	0.659	0.378	0.482	0.717	0.965
P10	0.378	0.482	0.379	0.455	0.447	0.551	0.447	0.551	0.482	0.586	0.000	0.158	0.659	0.732
P11	0.207	0.316	0.499	0.606	0.343	0.447	0.343	0.447	0.366	0.439	0.250	0.383	0.679	0.854
P12	0.060	0.231	0.743	1.000	0.120	0.274	0.207	0.316	0.293	0.366	0.060	0.231	0.659	0.732
P13	0.073	0.220	0.743	1.000	0.207	0.316	0.120	0.274	0.447	0.551	0.207	0.316	0.822	1.000
P14	0.293	0.366	0.682	0.758	0.366	0.439	0.482	0.586	0.482	0.586	0.378	0.482	0.717	0.965
P15	0.366	0.439	0.463	0.571	0.551	0.717	0.551	0.717	0.586	0.822	0.659	0.732	0.439	0.659
P16	0.717	0.965	0.455	0.682	0.822	1.000	0.822	1.000	0.439	0.659	0.659	0.732	0.439	0.659
P17	0.439	0.659	0.571	0.743	0.717	0.965	0.586	0.822	0.586	0.822	0.822	1.000	0.717	0.965
P18	0.482	0.586	0.499	0.606	0.366	0.439	0.586	0.822	0.366	0.439	0.659	0.732	0.659	0.732
P19	0.447	0.551	0.124	0.284	0.482	0.586	0.060	0.231	0.366	0.439	0.586	0.822	0.822	1.000
P20	0.343	0.447	0.000	0.076	0.447	0.551	0.220	0.293	0.482	0.586	0.439	0.659	0.439	0.659
AI	0.822	1.000	0.743	1.000	0.822	1.000	0.822	1.000	0.822	1.000	0.822	1.000	0.822	1.000

To obtain the weighted normalized decision matrix, the normalized matrix is multiplied by the weight coefficients corresponding to each criterion. This process is illustrated in Table 8.

Table 8
Weighted normalized matrix

	0.201		0.102		0.170		0.116		0.203		0.134		0.076	
	K_1		K_2		K_3		K_4		K_5		K_6		K_7	
AAI	0.012	0.044	0.000	0.008	0.020	0.047	0.007	0.027	0.059	0.074	0.000	0.021	0.033	0.050
P1	0.136	0.172	0.051	0.062	0.140	0.170	0.064	0.083	0.134	0.149	0.074	0.096	0.062	0.076
P2	0.165	0.201	0.058	0.076	0.112	0.124	0.083	0.112	0.089	0.134	0.046	0.060	0.050	0.056
P3	0.103	0.136	0.051	0.062	0.100	0.140	0.051	0.076	0.119	0.167	0.060	0.074	0.050	0.056
P4	0.090	0.111	0.031	0.039	0.082	0.100	0.060	0.079	0.146	0.196	0.059	0.088	0.062	0.076
P5	0.069	0.090	0.031	0.039	0.070	0.087	0.068	0.095	0.074	0.089	0.059	0.088	0.055	0.073
P6	0.074	0.088	0.039	0.046	0.094	0.122	0.064	0.083	0.074	0.089	0.078	0.110	0.050	0.056
P7	0.088	0.132	0.062	0.087	0.122	0.164	0.056	0.068	0.091	0.112	0.091	0.114	0.062	0.076
P8	0.132	0.147	0.058	0.076	0.112	0.124	0.079	0.099	0.167	0.203	0.016	0.037	0.055	0.073
P9	0.118	0.165	0.062	0.087	0.075	0.112	0.068	0.095	0.089	0.134	0.051	0.065	0.055	0.073
P10	0.076	0.097	0.039	0.046	0.076	0.094	0.052	0.064	0.098	0.119	0.000	0.021	0.050	0.056
P11	0.042	0.064	0.051	0.062	0.058	0.076	0.040	0.052	0.074	0.089	0.034	0.051	0.052	0.065
P12	0.012	0.047	0.076	0.102	0.020	0.047	0.024	0.037	0.059	0.074	0.008	0.031	0.050	0.056
P13	0.015	0.044	0.076	0.102	0.035	0.054	0.014	0.032	0.091	0.112	0.028	0.042	0.062	0.076
P14	0.059	0.074	0.070	0.077	0.062	0.075	0.056	0.068	0.098	0.119	0.051	0.065	0.055	0.073
P15	0.074	0.088	0.047	0.058	0.094	0.122	0.064	0.083	0.119	0.167	0.088	0.098	0.033	0.050
P16	0.144	0.194	0.046	0.070	0.140	0.170	0.095	0.116	0.089	0.134	0.088	0.098	0.033	0.050

Table 8
Continued

	0.201		0.102		0.170		0.116		0.203		0.134		0.076	
	K_1		K_2		K_3		K_4		K_5		K_6		K_7	
P17	0.088	0.132	0.058	0.076	0.122	0.164	0.068	0.095	0.119	0.167	0.110	0.134	0.055	0.073
P18	0.097	0.118	0.051	0.062	0.062	0.075	0.068	0.095	0.074	0.089	0.088	0.098	0.050	0.056
P19	0.090	0.111	0.013	0.029	0.082	0.100	0.007	0.027	0.074	0.089	0.078	0.110	0.062	0.076
P20	0.069	0.090	0.000	0.008	0.076	0.094	0.025	0.034	0.098	0.119	0.059	0.088	0.033	0.050
AI	0.165	0.201	0.076	0.102	0.140	0.170	0.095	0.116	0.167	0.203	0.110	0.134	0.062	0.076

The next step in this methodology involves calculating the weighted matrix sum (Si, shown in Table 9) and determining the utility degrees of the alternatives using expressions (18) and (19). Additionally, the rankings of the alternatives are derived based on these calculations. All results, including the weighted matrix sum, utility degrees, and alternative rankings, are comprehensively presented in Table 10.

Table 9
The values of Si

	Si				
A (AI)	0.132			0.271	
P1	0.661	0.807	P11	0.350	0.459
P2	0.604	0.762	P12	0.250	0.393
P3	0.534	0.711	P13	0.320	0.462
P4	0.529	0.688	P14	0.450	0.550
P5	0.425	0.562	P15	0.519	0.667
P6	0.473	0.595	P16	0.636	0.832
P7	0.572	0.753	P17	0.620	0.842
P8	0.619	0.759	P18	0.491	0.592
P9	0.516	0.731	P19	0.407	0.541
P10	0.390	0.496	P20	0.361	0.482
AID	0.815			0.1002	

Table 10
Results of Grey MARCOS method and alternative ranks

	$\otimes C_i^-$		$\otimes C_i^+$		$\otimes f(C_i^-)+\otimes f(C_i^+)$		$\otimes f(C_i^-)$		$\otimes f(C_i^+)$		Crisp $\otimes C_i^-$	Crisp $\otimes C_i^+$	Crisp $\otimes f(C_i^-)$	Crisp $\otimes f(C_i^+)$	$\otimes f(C)$	rank
P1	2.440	6.113	0.660	0.6596	3.100	6.772	0.133	0.133	0.492	1.233	4.276	0.660	0.133	0.863	0.643	1
P2	2.229	5.773	0.6025	0.6025	2.832	6.376	0.122	0.122	0.450	1.164	4.001	0.603	0.122	0.807	0.544	5
P3	1.970	5.381	0.5325	0.5325	2.503	5.913	0.107	0.107	0.397	1.085	3.675	0.533	0.107	0.741	0.436	7
P4	1.954	5.209	0.5282	0.5282	2.482	5.737	0.107	0.107	0.394	1.051	3.582	0.528	0.107	0.722	0.421	9
P5	1.570	4.256	0.4243	0.4243	1.994	4.680	0.086	0.086	0.317	0.858	2.913	0.424	0.086	0.588	0.269	14
P6	1.745	4.502	0.4717	0.4717	2.217	4.974	0.095	0.095	0.352	0.908	3.124	0.472	0.095	0.630	0.324	12
P7	2.113	5.705	0.5710	0.5710	2.684	6.276	0.115	0.115	0.426	1.151	3.909	0.571	0.115	0.788	0.500	6
P8	2.284	5.750	0.6174	0.6174	2.902	6.367	0.125	0.125	0.461	1.160	4.017	0.617	0.125	0.810	0.561	4
P9	1.907	5.534	0.5154	0.5154	2.422	6.049	0.104	0.104	0.385	1.116	3.720	0.515	0.104	0.750	0.426	8
P10	1.442	3.759	0.3896	0.3896	1.831	4.149	0.079	0.079	0.291	0.758	2.600	0.390	0.079	0.525	0.219	16
P11	1.293	3.473	0.3494	0.3494	1.642	3.822	0.070	0.070	0.261	0.700	2.383	0.349	0.070	0.481	0.179	18
P12	0.922	2.973	0.2491	0.2491	1.171	3.222	0.050	0.050	0.186	0.600	1.948	0.249	0.050	0.393	0.102	20
P13	1.183	3.497	0.3199	0.3199	1.503	3.817	0.065	0.065	0.239	0.705	2.340	0.320	0.065	0.472	0.160	19
P14	1.660	4.166	0.4486	0.4486	2.108	4.615	0.090	0.090	0.335	0.840	2.913	0.449	0.090	0.588	0.286	13
P15	1.916	5.047	0.5179	0.5179	2.434	5.564	0.104	0.104	0.386	1.018	3.481	0.518	0.104	0.702	0.400	10
P16	2.350	6.296	0.6350	0.6350	2.985	6.931	0.128	0.128	0.474	1.270	4.323	0.635	0.128	0.872	0.623	2
P17	2.289	6.374	0.6185	0.6185	2.907	6.992	0.125	0.125	0.462	1.286	4.331	0.619	0.125	0.874	0.607	3

Table 10
Continued

	$\otimes C_i^-$		$\otimes C_i^+$		$\otimes f(C_i^-)+\otimes f(C_i^+)$		$\otimes f(C_i^-)$		$\otimes f(C_i^+)$		Crisp $\otimes C_i^-$	Crisp $\otimes C_i^+$	Crisp $\otimes f(C_i^-)$	Crisp $\otimes f(C_i^+)$	$\otimes f(C)$	rank
P18	1.811	4.485	0.4895	0.4895	2.301	4.975	0.099	0.099	0.365	0.905	3.148	0.490	0.099	0.635	0.340	11
P19	1.501	4.099	0.4057	0.4057	1.907	4.504	0.082	0.082	0.303	0.827	2.800	0.406	0.082	0.565	0.247	15
P20	1.331	3.653	0.3598	0.3598	1.691	4.013	0.073	0.073	0.269	0.737	2.492	0.360	0.073	0.503	0.193	17

4. Comparative analysis

In this part of the paper, a comparative analysis of the results obtained in relation to the application of other methods was performed, and the results are shown in Figure 4. The obtained results indicate that by applying the model described in this paper, the first-ranked professor and the last-ranked professor retained their places in the application of other MCDM methods, while in the ranking of other professors, minor deviations were noticeable compared to the applied model Spherical Fuzzy AHP – Grey MARCOS.

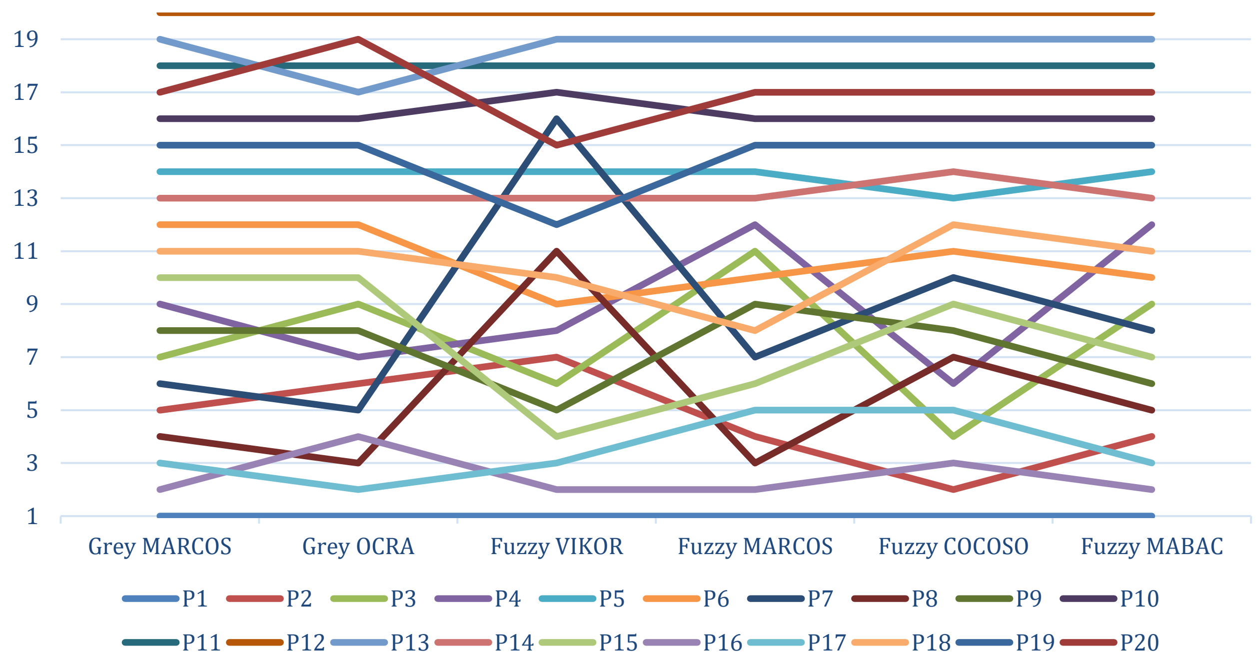

Fig. 4. Results of a comparative analysis of the application of different methods

5. Conclusions

The study demonstrates the effective integration of Spherical Fuzzy AHP and Grey MARCOS methods for evaluating university professors, offering a robust and systematic approach to multi-criteria decision-making. By defining precise weight coefficients for evaluation criteria through Spherical Fuzzy AHP and ranking alternatives with Grey MARCOS, the model addresses inherent uncertainties and subjectivities in the assessment process. The criteria, including teaching quality, accessibility to students, professional competence, and ethical behavior, were thoroughly analyzed, ensuring a holistic evaluation framework.

The results underline the reliability and adaptability of the hybrid model in identifying key strengths and weaknesses, supporting both individual professional development and institutional improvement. Compared to traditional methods, this approach ensures transparency, reduces bias, and provides actionable insights. The use of interval grey numbers further enhances precision, making the model particularly suitable for dynamic and diverse educational contexts.

This methodology promotes continuous quality improvement by offering detailed feedback to professors and supporting strategic planning for universities. It also fosters trust in the evaluation process among students, faculty, and administration. By bridging qualitative and quantitative aspects, the hybrid model contributes to raising academic standards and aligning them with global educational expectations. The results confirm the model's effectiveness and flexibility, underscoring its value for both individual evaluations and broader institutional enhancements. This methodology delivers actionable insights for improving teaching quality, fostering professional development, and enhancing institutional competitiveness. The findings highlight the significance of incorporating advanced MCDM techniques to ensure thorough and fair assessments in academia.

This study presents a practical framework for universities seeking to raise educational standards while tackling global challenges in higher education evaluation. By implementing this hybrid model, institutions can cultivate a culture of continuous improvement and achieve more consistent and meaningful outcomes in professor evaluations.

The successful application of this method paves the way for its use in other domains requiring nuanced decision-making. Future research could explore its application in broader institutional assessments and include additional criteria tailored to specific academic or professional settings.

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Conflicts of Interest
The authors declare no conflicts of interest.

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