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A Fuzzy AHP and PCA Approach to the Role of Media in Improving Education and the Labor Market in the 21st Century

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Abstract: In a hyperproductive interactive environment, where speed and cost-effectiveness often overshadow accuracy, the media's role is increasingly shifting towards an educational function, beyond its traditional informative and entertaining roles. This shift, particularly through the promotion of science and education, aims to bridge the gap between educational institutions and the labor market. In this context, the importance of 21st-century competencies—encompassing a broad range of knowledge and skills—becomes increasingly clear. Educational institutions are now expected to equip students with relevant, universally applicable, and market-competitive competencies. This paper proposes using a combination of principal component analysis (PCA) and fuzzy analytic hierarchy process (FAHP) to rank 21st-century competencies developed throughout the educational process to improve the system. The highest-ranked competency identified is the ability to manage information—specifically, gathering and analyzing information from diverse sources. It has been shown that respondents who developed “soft skills” and media literacy during their studies are better able to critically assess content on social networks and distinguish between credible and false information. The significance of this work lies in its focus on the damaged credibility of online media caused by user-generated content and the rapid spread of unverified and fake news. Denying such discourse or erasing digital traces is therefore futile. Developing a critical approach to information is essential for consistently identifying fake news, doctored images, and recordings taken out of context, as well as preventing their spread.

Keywords: media; education; labor market; competences; PCA analysis; AHP and FAHP analysis

MSC: 62H25; 03E72; 68U35



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1. Introduction

Key competencies involve integrating a transferable, multifunctional set of knowledge, skills, and attitudes that are essential for personal fulfillment, development, social inclusion, and employment. In this context, media literacy takes on particular importance as an ongoing process aimed at developing a variety of communication competencies to enable the effective selection and evaluation of media data and information.

The term “21st-century competencies” refers to a broad spectrum of knowledge, skills, work habits, and traits crucial for success in modern careers and workplaces. However, it is important to recognize that this concept encompasses a wide range of skills that are

not easily defined or formally codified, which can lead to varying interpretations. The concept emphasizes the need to impart essential, practical, and universally applicable skills and knowledge.

Possessing 21st-century skills is crucial for supporting sustainable careers. Karaca-Atik et al. [1] explored the relationship between specific skills and sustainable career outcomes as independent factors, highlighting the mechanisms that drive career development in the social sciences. By examining career sustainability as a multidimensional construct through three interconnected indicators—happiness, health, and productivity—they demonstrated the significant impact that acquired skills have on achieving sustainable careers. A sustainable career is understood as a personalized journey that integrates various experiences over time and navigates different social environments. This personal dimension is reflected in the decisions and actions of individuals [2]. In this context, it is essential to emphasize the need for a comprehensive body of knowledge that explicitly addresses the processes involved and the value generated. Sustainable knowledge practices must be grounded in responsible and ethical exchanges among diverse stakeholders [3]. Ultimately, these efforts hold meaning only when career development is strategically planned and employee satisfaction is prioritized; neglecting this can negatively impact employees' intentions to remain with the organization [4].

The concept of 21st-century competencies was developed in response to modern business demands for a balance between professional knowledge, skills, and soft competencies [5,6]. Contemporary educational approaches focus on developing interdisciplinary skills, which suggests that many educational institutions may still fall short in preparing students for success in the dynamic and evolving labor market of the 21st century.

The skills that were once acquired through education are often no longer sufficient to win quality jobs in the labor market. The inability to use new technologies by people who received their education a long time ago becomes more important than the enormous work experience that these people have, sometimes even leading to the search for a new job. Universities face a similar problem, as they have to keep up with the new demands of the labor market with the education they provide, offering courses that teach the new skills needed in this century, leaving aside some classical values [7].

One of the ways to define and determine the necessary skills for the successful fulfillment of 21st-century competencies is through multicriteria decision-making (MCDM) methods, having it as a useful tool for making informed decisions in the presence of multiple criteria, offering a nuanced perspective on the decision-making process, as well as enabling the analyst to convert linguistic definitions into mathematical expressions. For this purpose, Karakolis et al. [8] use the TOPSIS and PROMETHEE II methods. Also, a new model using interval-valued, hesitant fuzzy numbers [9] is used to determine the probability information and realize the conversion of fuzzy numbers to a cloud model.

Nowadays, social networks play a key role in the promotion of media, perhaps being the main platform for their promotion. A few key aspects that strengthen the role of the media are accessibility, interaction with the audience, content creation, speed, and timelines, as well as the ability to obtain a wealth of information for decision-making. Social networks are particularly useful in solving decision-making problems in large groups, especially in the era of big data [10]. The analysis of the influence of sociodemographic factors and knowledge on the labor market was presented in [11], while in [12], the authors deal with defects of information distortion, lack of trust, uncertainty, and randomness and the role of decision-makers in large group decision-making.

In this context, the role of human resource management is crucial, focusing on developing differentiated strategies for attracting and selecting talent with the right skills. This shift moves the focus from individual communication channels to target groups with clearly identifiable habits, needs, and opportunities. Digital media, with their multimedia features and interactivity, provide fast and cost-effective communication channels without the rigid structure of traditional media, significantly expanding the reach to a larger pool of potential job candidates.

The mismatch between knowledge and skills becomes particularly evident during the candidate selection process for open positions. At this stage, gaps in education, lack of skills, outdated knowledge, and even overqualification are often observed when workers are hired for roles that do not require their formal educational qualifications. This deficit of adequate human capital directly impacts productivity, reducing the output per worker and increasing average labor costs. Additionally, companies experience lower profitability as they are forced to invest in extra training and recruitment, which weakens their competitiveness. Perić et al. [13] highlight the importance of employee motivation and satisfaction, emphasizing that this is key to ensuring their full commitment to completing tasks and achieving the company's goals.

In the literature, the differentiation of skills is most often made between cognitive and noncognitive skills or soft skills. Cognitive skills encompass the ability to understand a situation and the actions that need to be taken in a given context, while noncognitive skills integrate attitudes and practices that an individual establishes towards themselves and others, sets and achieves goals, and makes responsible decisions [14]. Soft skills are recognized through emotional harmony with oneself, the building of positive relationships with others, managing people and conflicts as well as strategic thinking. In this sense, the concept of interpersonal intelligence is introduced, which is said to represent the vital signals of instinctive feelings that an individual perceives [15].

To explore the representation of 21st-century competencies among recent graduates, respondents were asked to rate the extent to which they felt these competencies were developed during their studies. The following key competencies were analyzed: creativity/innovation (X24), critical thinking (X28), problem-solving ability (X26), flexibility and adaptability (X25), teamwork (X14), communication skills (X17), basic computer skills (X23), information management (X21), research and inquiry skills (X22), ability to apply knowledge in practice (X27), leadership and responsibility (X13), initiative and self-management (X18), learning ability (X12), organizational and planning skills (X15), ability to criticize and self-criticize (X16), and self-motivation (X11).

Creativity in the media industry involves a complex thought process aimed at producing new educational ideas or products that are likely to possess comparative persuasiveness. A creative idea can be embraced if it is innovative and provides a solution to a specific issue. The constantly evolving media landscape, while subject to both positive and negative perspectives, proved invaluable during the period of social isolation caused by the coronavirus. This was especially evident in tertiary education, where online teaching was more effectively implemented, acknowledging that students are often oriented towards independent research activities and academic writing.

To best adapt to this new virtual reality, pupils and students are expected to master three essential skills—perception, emotional management, and self-regulation—alongside nine specific practical skills: cognitive ability, effective Internet use, self-awareness, beliefs, motivation, anxiety management, self-perception, concentration, and time management.

In [16], competencies and PCA analysis were examined, explaining the overall variance of the set of competencies (components), i.e., variability within groups, where the components after Oblimin rotation showed moderate intercorrelation and the analysis of the structure matrix showed good discrimination between factors. The components are obtained, and their factor weights (which indicate the relative importance of each item in defining the component, which is the correlation coefficient between the item and the component) within the group, as well as the part of the variance, are explained by common factors (communalities). We also concluded that, depending on the interests of the students, it is important to categorize competencies to prioritize them in the educational context. In this paper, the use of the fuzzy AHP is conducted to investigate (and verify) previously obtained results, comparing obtained weights inside the groups and overall.

Primary research was designed to test the following hypotheses:

H₁: A quality education has a positive effect on the development of an individual's "soft competence".

H₂: Ranking of competencies according to the AHP and FAHP methods (five variants) gives similar results.

H₃: Improving the media literacy of young people contributes to the improvement of media content.

The advances in this paper are summarized in the following:

- The PCA and fuzzy AHP analysis are conducted to determine the rank of soft and core competencies of the 21st-century competencies.
- The estimation and analysis of ranking similarities are conducted and discussed.

The rest of the paper is organized as follows: Section 2 presents sample, data, and attitude analysis, while Sections 3 and 4, respectively, deal with principal component analysis, and fuzzy AHP analysis. The results (of the FAHP) are given in Section 5, and the analysis of media discourse is in Section 6. Section 7 deals with results and discussion, while Section 8 is determined for the managerial aspect. The conclusion is presented in Section 9.

2. Sample, Data, and Attitude Analysis

The data was collected via a survey using Google Forms. The research sample consisted of a purposive sampling of newly graduated students from two private faculties in the Republic of Serbia. A pilot survey was conducted with 45 respondents. After analyzing the pilot study, which included checking the content validity of all measured aspects, the final version of the survey was developed and administered to a new group of 252 respondents ($n = 252$). Data collection took place in June and July 2024.

The first part of the survey gathered general demographic information. In the second part, respondents assessed, on a scale, the extent to which certain competencies were developed during their course of study, specifically evaluating the educational institution's role in that development. The third section focused on respondents' views regarding the importance of media in the educational process.

Part of the data was processed using the SPSS 19 software package, while AHP and FAHP analyses were conducted using Excel.

3. Principal Component Analysis

A total of 252 respondents participated in the study, with 41.3% male and 58.7% female. Of the 252 respondents, 213 reported their average grades during their studies: 30.5% had an excellent grade, 45.1% above average, 19.7% average, and 4.7% below average.

To explain the common variance in the set of variables or the variability within groups of variables, factor analysis using principal component analysis (PCA) will be applied. This method is based on a mathematical model where the factors are derived as standardized principal components. By examining the correlation matrix among the variables, 16 variables were included in the analysis to assess the data's suitability, representing the respondents' positive and negative opinions.

The general factor model has the following form:

$$X_i = a_{i1}F_1 + a_{i2}F_2 + \dots + a_{im}F_m + e_i, \quad (1)$$

where:

X —the value of a variable with an arithmetic mean of zero and a variance of one;

i —serial number of the variable;

F —mutually independent factors;

m —ordinal number of factors;

a —factor load;

e —specific factor related only to the given variable.

All criteria were met: the Kaiser–Meyer–Olkin Measure of sampling adequacy was 0.897, and Bartlett's test of sphericity showed statistical significance ($\text{sig} < 0.001$), justifying

the use of factor analysis. The principal component analysis revealed four components with eigenvalues greater than 1 (9.96, 1.34, 1.11, and 1.02), collectively explaining 65.53% of the variance. The existence of the first breaking point between the second and third components was observed on the curve diagram.

To determine the appropriate number of factors to retain, a parallel analysis was conducted. Based on the results of the parallel analysis and the SPSS component matrix, it was concluded that a two-factor solution was more suitable. After applying Varimax rotation, the following components were identified:

Component 1: Self-motivation; Ability to learn; Leadership and responsibility; Teamwork; Organizational and planning skills; Communication; Ability to critique and self-critique; Initiative and self-management.

Component 2: Information management (gathering and analyzing data from various sources); Research skills; Basic computer proficiency; Creativity and innovation; Flexibility and adaptability; Problem-solving; Practical application of knowledge; Critical thinking.

The results support dividing the skills into two groups of components. The first group corresponds to static competencies, representing an individual's innate cognitive ability to manage and understand different behaviors effectively. The second group represents dynamic competencies, which rely on external factors to enhance their applicability by the individual.

To rank each competency, both within the group and overall, the AHP and FAHP methods will be applied.

4. Fuzzy AHP Analysis

In this section, some basic information about AHP and fuzzy AHP is given as well as the algorithm describing the FAHP.

4.1. A Short Introduction to AHP and FAHP

The challenge of selecting the most effective assessment for criteria and indicators has been addressed through the use of multicriteria, decision-making methods, which play a crucial role in various aspects of life. The analytic hierarchy process (AHP), developed by Thomas L. Saaty in the early 1980s, is a multicriteria method that aids decision-making involving conflicting criteria and alternatives. AHP has been rigorously studied and refined in numerous scientific publications. The method is grounded in several key axioms: the reciprocity axiom, the homogeneity axiom, the dependency axiom, and the axiom of expectations. In essence, AHP is a technique that decomposes complex problems into a hierarchical structure, with the ultimate goal at the top and criteria, subcriteria, and alternatives arranged below. This flexible method allows for the exploration of complex problems with multiple criteria and alternatives, making it relatively straightforward to identify relationships among influencing factors and assess their relative importance in practical contexts. A core feature of AHP is that decision-makers view issues as elements within a mutual hierarchical framework, where the highest level represents their primary objective, supported by subordinate criteria that are vital to the decision-making process. AHP is particularly valuable for pairwise comparisons among the elements of the hierarchy, including goals, criteria, and alternatives. However, when applying the crisp AHP method, uncertainty can arise for experts when establishing the pairwise comparison matrix. Even a single expert may struggle to quantify the importance of one criterion over another consistently. For instance, should an expert assign a value of $m_{ij} = 2$ or $m_{ij} = 3$ when one element is weakly dominant over another? If values $m_{ik} = 4$ and $m_{kj} = 5$ are given for comparing elements M_i and M_k , and M_k and M_j , respectively, how can one then set $m_{ij} = m_{ik} \cdot m_{kj} = 20$ for comparing elements M_i and M_j when Saaty's scale only goes up to 9? These challenges become even more pronounced with multiple experts involved. Consequently, there is a need to incorporate the handling of uncertain data within the AHP framework.

For more than half a century, one of the useful tools to deal with uncertainty and imprecise linguistic statements, the fuzzy sets theory, represents a significant support to decision-making problems [17,18]. Primarily, the aim of fuzzy sets, the generalization of non-fuzzy sets, was the mathematical presentation of linguistic variables, enabling the decision-maker to make a model for partially unknown or incomplete information [19,20]. In crisp set theory, the element belongs to a set or not, while in the theory of fuzzy sets, the membership function (MF), usually denoted by μ is introduced. It serves to map each element of the universal set into the interval $[0, 1]$, determining the degree of belongingness of an element to a fuzzy set. Let all fuzzy sets be defined on the set of real numbers \mathbb{R} to be denoted as $FS(\mathbb{R})$. The number $G \in FS(\mathbb{R})$ is a fuzzy number if $x_0 \in \mathbb{R}$ exists, so it holds that $\mu_G(x_0) = 1$ and for every $\lambda \in [0, 1]$, $G_\lambda = [x, \mu_{G_\lambda}(x) \geq \lambda]$ is a closed interval [21].

The fundamental part of a triangular fuzzy number (TFN), its membership function, is defined as follows

$$\mu_{TFN}(x) = \begin{cases} \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{u-x}{u-m}, & m \leq x \leq u \\ 0, & \text{otherwise,} \end{cases} \tag{2}$$

where inequality $l \leq m \leq u$ holds. Numbers $l, m,$ and u serve as the lower, middle, and upper values of G , respectively, while for $l = m = u$, TFN becomes a crisp number. The usual notation of the triangular fuzzy number will be $\tilde{G} = (l, m, u)$.

The left and right sides of the membership function $\mu_{TFN}(x)$ of TFN $\tilde{G} = (l, m, u)$, $\mu_{\tilde{G}}^l$ and $\mu_{\tilde{G}}^r$, as well as their matching inverse functions $(\mu_{\tilde{G}}^l)^{-1}$ and $(\mu_{\tilde{G}}^r)^{-1}$ are respectively defined as $\mu_{\tilde{G}}^l = \frac{x-l}{m-l}$, $\mu_{\tilde{G}}^r = \frac{u-x}{u-m}$, $(\mu_{\tilde{G}}^l)^{-1} = l + (m-l)y$, $(\mu_{\tilde{G}}^r)^{-1} = u + (m-u)y$, $y \in [0, 1]$. The total integral value, as a combination of left and right integral values, is determined as follows [22]:

$$\begin{aligned} I_T^\lambda(\tilde{G}) &= \lambda I_R(\tilde{G}) + (1-\lambda)I_L(\tilde{G}) = \lambda \int_0^1 (\mu_{\tilde{G}}^r)^{-1} dy + (1-\lambda) \int_0^1 (\mu_{\tilde{G}}^l)^{-1} dy = \\ &= \frac{1}{2}\lambda(m+u) + \frac{1}{2}(1-\lambda)(m+l) = \frac{1}{2}(\lambda u + m + (1-\lambda)l), \end{aligned} \tag{3}$$

where λ , an optimism index, i.e., the attitude of an expert during the decision-making process. The pessimistic point of view is presented taking the value $\lambda = 0$, from where it is obtained that $I_T^0(\tilde{G}) = I_L(\tilde{G})$, for the value $\lambda = 1$, the optimistic point of view is given, and $I_T^1(\tilde{G}) = I_R(\tilde{G})$. For $\lambda = 0.5$, the balanced (moderate) attitude of the decision-maker is granted, and $I_T^{0.5}(\tilde{G}) = \frac{1}{2}(I_L(\tilde{G}) + I_C(\tilde{G}))$. There are also, recently introduced, semipessimistic and semi-optimistic points of view obtained for $\lambda = 0.25$ and $\lambda = 0.75$, respectively [23].

The main unary (scalar multiplication and inverse) and binary (addition, subtraction, and multiplication) operations for TFNs $G_1 = (l_1, m_1, u_1)$ and $G_2 = (l_2, m_2, u_2)$ and scalar $k > 0, k \in \mathbb{R}$ are shown below [24,25]:

$$\begin{aligned} \tilde{G}_1 \oplus \tilde{G}_2 &= (l_1, m_1, u_1) \oplus (l_2, m_2, u_2) = (l_1 + l_2, m_1 + m_2, u_1 + u_2), \\ \tilde{G}_1 \ominus \tilde{G}_2 &= (l_1, m_1, u_1) \ominus (l_2, m_2, u_2) = (l_1 - l_2, m_1 - m_2, u_1 - u_2), \\ \tilde{G}_1 \otimes \tilde{G}_2 &= (l_1, m_1, u_1) \otimes (l_2, m_2, u_2) = (l_1 \cdot l_2, m_1 \cdot m_2, u_1 \cdot u_2), \\ k \cdot \tilde{G}_1 &= (k \cdot l_1, k \cdot m_1, k \cdot u_1), \\ \tilde{G}_1^{-1} &= (l_1, m_1, u_1)^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1}\right). \end{aligned}$$

4.2. The Steps of the FAHP Algorithm

In the sequel, the steps of the fuzzy analytic hierarchy process are summarized [21,26]:

Step 1: Establishing the main goal and hierarchical appearance of criteria.

The hierarchical structure, with the main goal as the most important component, at the top, has been organized vertically. The criteria and subcriteria affecting the goal are at the intermediate levels, with alternatives at the lowest level.

Step 2: Setting the matrix \tilde{H} in terms of triangular fuzzy numbers.

Criteria and subcriteria are used during pairwise comparisons, enabling the creation of the matrix $\tilde{H} = (\tilde{h}_{ij})_{n \times n}$. The total of $n(n - 1)/2$ comparisons of elements from a higher level with elements from a lower level are made. Using triangular fuzzy numbers (TFNs), the hierarchy and comparison are given, where \tilde{h}_{ij} is a fuzzy value representing the relative importance of one criterion to another. It holds that $\tilde{h}_{ii} = (1, 1, 1)$, when comparing criteria to itself, and $\tilde{h}_{ij} = 1/\tilde{h}_{ji}$ for $i \neq j$.

The fuzzy scale, TFNs, and their explanations used to enable pairwise comparisons are given:

TFN $\tilde{1}$: "Two criteria are equally important" = (1, 1, 3)

TFN $\tilde{3}$: "One criterion is slightly more important than another" = (1, 3, 5)

TFN $\tilde{5}$: "One criterion is strongly more important than another" = (3, 5, 7)

TFN $\tilde{7}$: "One criterion is very strongly more important than another" = (5, 7, 9)

TFN $\tilde{9}$: "One criterion is absolutely strongly more important than another" = (7, 9, 9), $\tilde{2} = (1, 2, 3)$, $\tilde{4} = (3, 4, 5)$, $\tilde{6} = (5, 6, 7)$, and $\tilde{8} = (7, 8, 9)$ are intermediate values used when compromise is needed [27,28]. The graphic representation of the used FAHP scale with lower, median, and upper values is presented in Figure 1.

Step 3: Matrix consistency calculation.

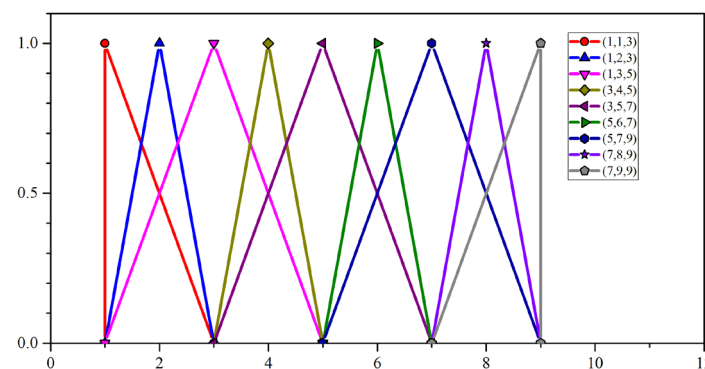


Figure 1. Graphic representation of triangular fuzzy numbers.

For matrix $H = (h_{ij})_{n \times n'}$, we calculate the consistency index CI and consistency ratio CR using formulas

$$CI = \frac{\lambda_{max} - n}{n - 1}, CR = \frac{CI}{RI} \tag{4}$$

where λ_{max} represents maximal eigenvalue of matrices H . The random index RI determined by the matrix size and corresponding value is shown as

$$RI = \{(3, 0.58), (4, 0.9), (5, 1.12), (6, 1.24), (7, 1.32), (8, 1.41), (9, 1.45), (10, 1.49)\} \tag{5}$$

The value $CR < 0.1$ verifies the matrix H consistency, while differently, the reason for inconsistency should be determined and all calculations repeated.

Step 4: The fuzzification process.

Applying formulas

$$D = \sum_{i=1}^n \sum_{j=1}^n \tilde{h}_{ij} = \sum_{i=1}^n \sum_{j=1}^n (l_{ij}, m_{ij}, u_{ij}) \tag{6}$$

and

$$D^{-1} = \left(\sum_{i=1}^n \sum_{j=1}^n \tilde{h}_{ij} \right)^{-1} = \left(\frac{1}{\sum_{i=1}^n \sum_{j=1}^n u_{ij}}, \frac{1}{\sum_{i=1}^n \sum_{j=1}^n m_{ij}}, \frac{1}{\sum_{i=1}^n \sum_{j=1}^n l_{ij}} \right) \tag{7}$$

on triangular fuzzy numbers from the matrix $H = (h_{ij})_{n \times n}$, the Chang synthetic fuzzy number

$$\tilde{S}_i = (l_i, m_i, u_i) = \sum_{j=1}^n \tilde{h}_{ij} \otimes D^{-1}, i = \overline{1, n} \tag{8}$$

is obtained [24].

Step 5: The defuzzification process.

Applying the formula

$$w_i = I_T^\lambda(\tilde{S}_i) = 0.5(\lambda u_i + m_i + (1 - \lambda)l_i), i = \overline{1, n}, \lambda \in [0, 1] \tag{9}$$

on obtained TFNs $\tilde{S}_i, \overline{1, n}$, the total integral value is calculated.

Step 6: Vector normalization and criteria weight calculation.

The weight vector $w = (w_1, w_2, \dots, w_n)^T$ is normalized using the formula

$$w_i^* = w_i \left(\sum_{i=1}^n w_i \right)^{-1} \tag{10}$$

After this, criteria ranking is performed.

AHP, as a method characterized by objectivity, flexibility, and simple interpretation, provides decision-makers with structure and systematic approaches in the process of problem decomposition. It helps them clarify their goals, involve relevant stakeholders, quantify preferences, and analyze the consequences of decisions, thereby increasing the likelihood of making informed and rational choices (see Figure 2).

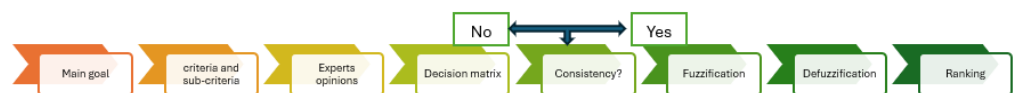


Figure 2. Graphic representation of decision-making.

Some of the various applications of FAHP could be seen in the area of shopping mall site selection [29], global supplier risk factors [30], strategic marketing information systems [31], social networks [10], construction (of tunnels) [32], occupational hazards in the aquaculture sector [33], and many other areas.

5. Results for the FAHP

Each criterion and sub-criterion plays a unique role in the decision-making process. We will elaborate on how these factors are weighted and the implications of their interactions within the hierarchy. A comprehensive comparison will be made between the rankings derived from AHP and FAHP. The cases where significant discrepancies arise and the underlying reasons, such as differences in the treatment of vague or imprecise data in FAHP compared to the crisp evaluations of AHP, will be examined, hoping that our enhanced discussion will provide a clearer understanding of how the choice between AHP and FAHP can impact the decision-making process, ultimately leading to more informed and effective decisions.

In this section, the fuzzy AHP algorithm has been applied. The pairwise comparison matrices are made following the PCA factor analysis and opinions of the experts. The four experts (decision-makers) with more than 15 years of experience in the fields of Education, Economics and Statistics, Management, and Social Sciences, respectively, achieved a partial consensus in giving assessments [34].

The appropriate fuzzy comparison matrices are created, and their consistency checked.

Firstly, the main criteria ranking was discussed, both for AHP and FAHP, with five points of view (pessimistic, semipessimistic, balanced, semi-optimistic, and optimistic). Afterward, we rank individual subcriteria. Finally, we conduct the ranking of all sixteen subcriteria using the FAHP.

The results of the criteria ranking in terms of core skills and soft skills obtained using the FAHP method have been represented in the following tables.

In the AHP case, the weights of the main criteria, the core skills and the soft skills, named X1 and X2, respectively, are both equal to 0.5. The weights in the FAHP case are presented in Table 1, showing the dominance of soft skills, with its highest value equal to 0.607143 (in the case of the optimistic point of view, $\lambda = 1$). In the balanced point of view, the weight of criteria X2 is 1.39 times higher than the value of criteria X1, similar to $\lambda = 0$, in which case the quotient X2/X1 is equal to 1.15.

Table 1. Fuzzy comparison matrix and weights for the main criteria (CI = CR = 0).

	X2	X1	$\lambda = 0$	$\lambda = 0.25$	$\lambda = 0.5$	$\lambda = 0.75$	$\lambda = 1$
X2	$\tilde{1}$	$\tilde{1}$	0.535714	0.5625	0.581633	0.595982	0.607143
X1	$\tilde{1}^{-1}$	$\tilde{1}$	0.464286	0.4375	0.418367	0.404018	0.392857

A pairwise comparison matrix for subcriteria X1 and their weights are given in Tables 2 and 3 and Figure 3.

Table 2. Fuzzy comparison matrix for the subcriteria X1 (CI = 0.022, CR = 0.015).

X1	X11	X12	X13	X14	X15	X16	X17	X18
X11	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{4}$	$\tilde{5}$	$\tilde{6}$	$\tilde{6}$	$\tilde{6}$
X12	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{4}$	$\tilde{5}$	$\tilde{5}$	$\tilde{5}$
X13	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{4}$	$\tilde{4}$	$\tilde{4}$
X14	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{3}$	$\tilde{3}$
X15	$\tilde{5}^{-1}$	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}$	$\tilde{2}$	$\tilde{2}$
X16	$\tilde{6}^{-1}$	$\tilde{5}^{-1}$	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{1}$	$\tilde{1}$
X17	$\tilde{6}^{-1}$	$\tilde{5}^{-1}$	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}^{-1}$	$\tilde{1}$	$\tilde{1}$
X18	$\tilde{6}^{-1}$	$\tilde{5}^{-1}$	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}^{-1}$	$\tilde{1}^{-1}$	$\tilde{1}$

Table 3. The weights for the subcriteria X1.

X1	AHP	FAHP				
		$\lambda = 0$	$\lambda = 0.25$	$\lambda = 0.5$	$\lambda = 0.75$	$\lambda = 1$
X11	0.336361	0.305779	0.290797	0.281514	0.275198	0.270623
X12	0.227854	0.222565	0.223287	0.223735	0.22404	0.224261
X13	0.151707	0.16954	0.166803	0.165108	0.163954	0.163118
X14	0.099424	0.105078	0.114543	0.120408	0.124398	0.127289
X15	0.063884	0.07185	0.074046	0.075406	0.076331	0.077002
X16	0.040257	0.044577	0.048782	0.051388	0.05316	0.054445
X17	0.040257	0.041729	0.043508	0.04461	0.045359	0.045902
X18	0.040257	0.038882	0.038233	0.037832	0.037558	0.03736

In both AHP and all five FAHP cases, subcriteria X11, named self-motivation to work, ranked highest, while subcriteria X18, ranked lowest (in the AHP case, criteria X16–X18 have the same weight). This is somehow expected since the inner motivation represents “spiritus movens” of all important works and results achieved [35]. The criteria X12, the ability to learn and X13, representing leadership abilities, hold the second and third place of the core skills with the weights 0.227854 and 0.15171 in the AHP case,

0.22374 and 0.16511 in the balanced, and 0.22426 and 0.16312 in the optimistic FAHP case. Communicativeness, being the seventh-ranked subcriteria in this group has weights of 0.04351 and 0.04536 in the semipessimistic and semi-optimistic FAHP case, as can be seen in Figure 1. Comparing points of view for the X1 group of subcriteria, one can observe that the optimistic point of view (i.e., $\lambda = 1$) does not always yield a higher rank compared to the pessimistic point of view. For instance, for X13 and X18, the third and the eighth-ranked subcriteria, the pessimistic point of view ranked higher when compared to the corresponding optimistic one.

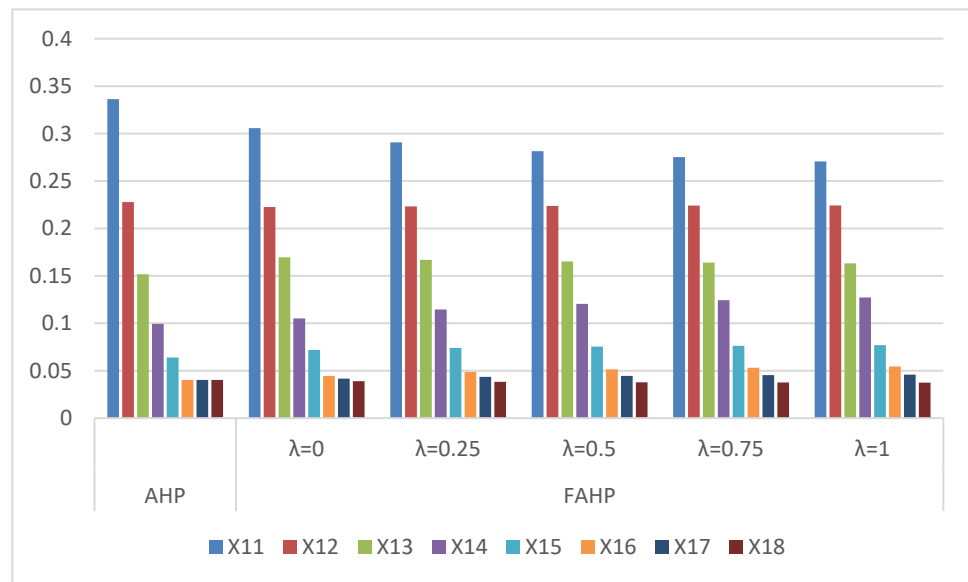


Figure 3. The weights of the core skills subcriteria X1.

For adopted soft skills subcriteria, the hierarchy is formed, and a matrix of subcriteria comparisons is presented in Table 4. The ranking of subcriteria is conducted in the same manner as in the case of core skills, with different weights for all subcriteria. The ability to manage information (gather and analyze them), subcriteria X21, has the highest weight, 0.3417 in the AHP case, followed by subcriteria X22 and X23, representing the research and basic computer skills. The moderate point of view (FAHP case) of those subcriteria yields the weights 0.27332, 0.21888, and 0.16961, respectively (see Table 5).

Table 4. Fuzzy comparison matrix for the subcriteria X2 (CI = 0.043, CR = 0.029).

X2	X21	X22	X23	X24	X25	X26	X27	X28
X21	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{4}$	$\tilde{5}$	$\tilde{6}$	$\tilde{7}$	$\tilde{8}$
X22	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{4}$	$\tilde{5}$	$\tilde{6}$	$\tilde{7}$
X23	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{4}$	$\tilde{5}$	$\tilde{6}$
X24	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{4}$	$\tilde{5}$
X25	$\tilde{5}^{-1}$	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$	$\tilde{4}$
X26	$\tilde{6}^{-1}$	$\tilde{5}^{-1}$	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}$	$\tilde{3}$
X27	$\tilde{7}^{-1}$	$\tilde{6}^{-1}$	$\tilde{5}^{-1}$	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$	$\tilde{2}$
X28	$\tilde{8}^{-1}$	$\tilde{7}^{-1}$	$\tilde{6}^{-1}$	$\tilde{5}^{-1}$	$\tilde{4}^{-1}$	$\tilde{3}^{-1}$	$\tilde{2}^{-1}$	$\tilde{1}$

In the middle of the ladder are the subcriteria X24 and X25, referring to creativity and the ability to adapt in new situations, with corresponding weights of 0.1032 and 0.6802 (AHP case) and 0.12133 and 0.0853, and 0.12959 and 0.09205 for pessimistic and optimistic point of view (FAHP), respectively.

Table 5. The weights for the subcriteria X2.

X2	AHP	FAHP				
		$\lambda = 0$	$\lambda = 0.25$	$\lambda = 0.5$	$\lambda = 0.75$	$\lambda = 1$
X21	0.341698	0.287605	0.278961	0.273317	0.269342	0.266391
X22	0.232039	0.222934	0.220481	0.218879	0.217751	0.216913
X23	0.155452	0.169731	0.169658	0.169611	0.169578	0.169553
X24	0.103201	0.121333	0.124698	0.126895	0.128443	0.129592
X25	0.068017	0.085303	0.08805	0.089844	0.091107	0.092045
X26	0.045005	0.054342	0.058298	0.060882	0.062702	0.064053
X27	0.030938	0.035982	0.037025	0.037705	0.038185	0.038541
X28	0.02365	0.022771	0.022829	0.022866	0.022893	0.022913

The final sequence of influencing subcriteria (with weights) in core skills and soft skills obtained using the FAHP method can be seen in Figure 4.

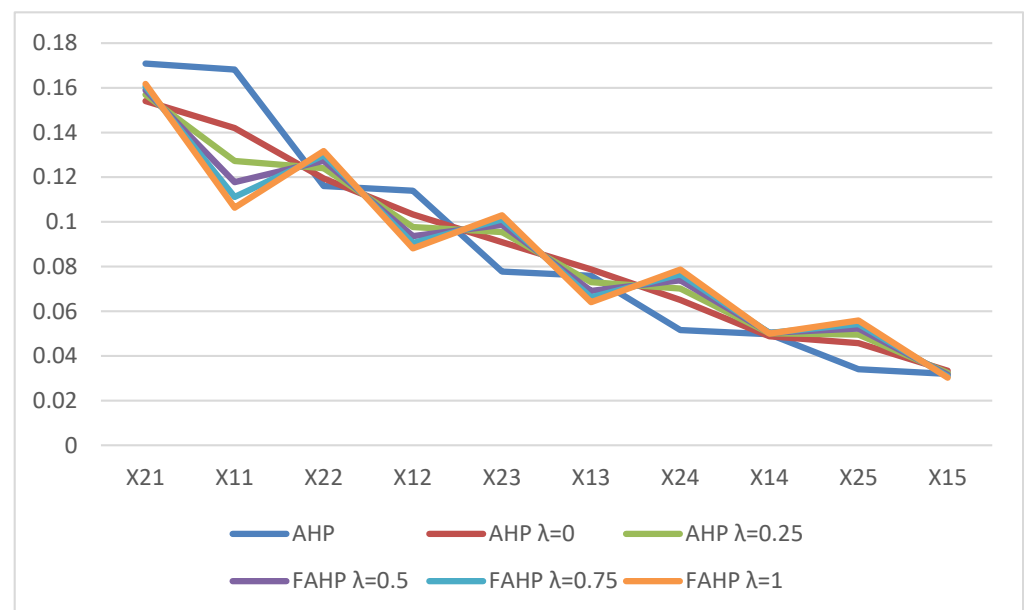


Figure 4. Graphical representation of final weights of most influential core skills and soft skills subcriteria obtained using the AHP and FAHP method with different degrees of optimism.

The results were obtained by applying the classical AHP and FAHP methods, whether they are an optimistic or pessimistic point of view; the most influential subcriteria was the Ability to manage information—gathering and analyzing information from various sources. Differences can be seen in the second ranking subcriteria, favoring self-motivation to work in the AHP and pessimistic part of the FAHP, and Research and inquiry—research skills in the second half of the FAHP. Similar situations stand for the fourth and fifth place, having the ability to learn, and basic computer skills. The end of the ladder is reserved for critical thinking in all cases. Initiative and self-management, the ability to apply knowledge in practice, the ability to criticize and self-criticize, and communicativeness have the lowest weights, with a slight difference in their ordering for AHP and different degrees of optimism in the FAHP case. The most influential subcriteria for different scenarios are given in Figure 5. One can see that in the case of AHP and the pessimistic point of view of the FAHP, the first five criteria have the same ranking. A similar situation is in the case of the balanced and optimistic point of view of the FAHP. Considering the ranking of criteria in the AHP compared to all five rankings in the FAHP, it can be concluded that there are no significant differences. There are minor ranking discrepancies between AHP and FAHP,

changing the criteria position of one up or down, often maintaining the same ranking order of several criteria.

Crisp approach AHP	1. Ability to manage information - gathering and analyzing information from various sources
	2. Self-motivation to work
	3. Research and inquiry - research skills
	4. Ability to learn
	5. Basic computer skills
BALANCED SCENARIO FAHP	1. Ability to manage information - gathering and analyzing information from various sources
	2. Research and inquiry - research skills
	3. Self-motivation to work
	4. Basic computer skills
	5. Ability to learn
PESSIMISTIC SCENARIO FAHP	1. Ability to manage information - gathering and analyzing information from various sources
	2. Self-motivation to work
	3. Research and inquiry - research skills
	4. Ability to learn
	5. Basic computer skills
OPTIMISTIC SCENARIO FAHP	1. Ability to manage information - gathering and analyzing information from various sources
	2. Research and inquiry - research skills
	3. Self-motivation to work
	4. Basic computer skills
	5. Ability to learn

Figure 5. The most influential subcriteria singled out for AHP and FAHP.

Different solving techniques have been applied in this paper, which in general, can lead to inconsistencies or disagreement. For the purpose of estimation and analysis of ranking similarities applying the AHP and the FAHP to all subcriteria influencing soft and hard skills, as well as to assess the accuracy and validity of the proposed model, we have conducted fifteen different rankings using the Spearman rank correlation coefficient: [36]:

$$r_s = 1 - \frac{6 \sum_{i=1}^n d_i^2}{n(n^2 - 1)}, \quad d_i = R_{x_i} - R_{y_i}, \quad (11)$$

where n is the number of elements in the ranking and R_{x_k} R_{x_i} and R_{y_i} represent the ranks of the k -th element in the compared rankings.

By applying the previous equation, all compared results are presented in Figure 6, and since $\min\{r_s\} = 0.99461$, it can be concluded that all rankings have high similarity [37]. The lowest value of the coefficient r_s for the AHP is when it is compared to FAHP ($\lambda = 0.5$, $\lambda = 0.75$, and $\lambda = 1$) and is equal to 0.99461. Comparing the ranking similarity between the pessimistic point of view of the FAHP, the lowest obtained value is 0.99608 (for $\lambda = 0.5$, $\lambda = 0.75$, and $\lambda = 1$). The same ranking of all subcriteria is obtained for FAHP ($\lambda = 0.5$) with FAHP ($\lambda = 0.75$) and FAHP ($\lambda = 1$), yielding the value $r_s = 1$.

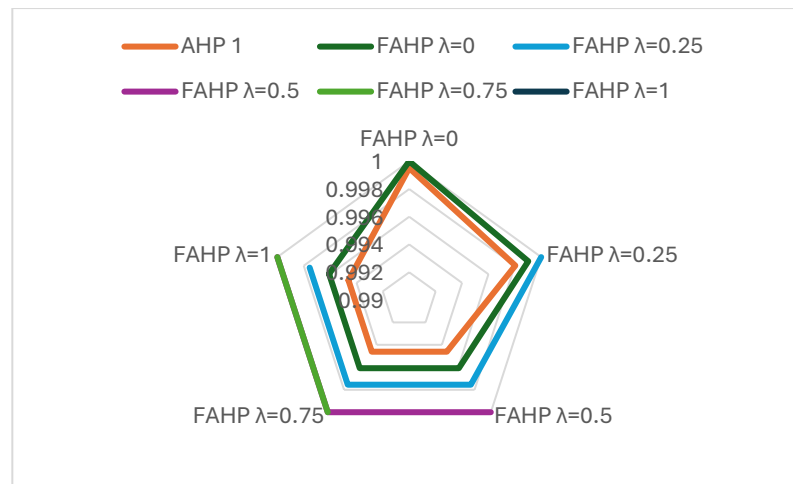


Figure 6. Ranking similarity.

6. Analysis of Media Discourse

According to the respondents, the majority (69.5%) believe that social networks are the primary platform for media promotion, followed by television (23.2%), print media (5.8%), and radio (1.5%). No statistically significant gender differences were observed regarding the evaluation of media promotion. Among social networks, YouTube is considered the most influential, with an average rating of 5.49, followed by Instagram at 5.08 and Facebook at 4.60. Notably, 50% of respondents rated YouTube a 7 for content promotion.

The Mann–Whitney U test revealed a statistically significant difference in the credibility assessment of content posted on LinkedIn between male ($Me = 3.0, n = 84$) and female respondents ($Me = 4.0, n = 79$), $U = 2253.50, z = -3.580, p = 0.006$. The size of the impact $r = \frac{z}{\sqrt{N}} = \frac{3.580}{\sqrt{163}} = 0.28$ that is, it can be said that the impact is medium [38]. The mean rank for females was higher.

The social networks that young people rated as the most credible in the promotion of media content (Facebook, Instagram, and YouTube) show a significant direct mutual linear connection, i.e., correlation coefficients belong to the interval $0.5 < r < 0.7$. For further details, refer to Table 6.

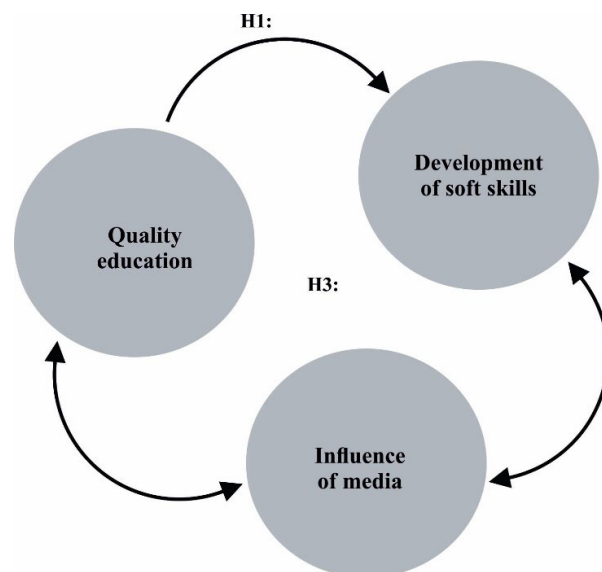
Table 6. Correlations.

	1	2	3
1. Assess the credibility of social networks in marketing media content (rate on a scale): Facebook	-		
2. Assess the credibility of social networks in marketing media content (rate on a scale): Instagram	0.621 **	-	
3. Assess the credibility of social networks in marketing media content (rate on a scale): YouTube	0.608 **	0.650 **	-

** Correlation is significant at the 0.01 level (2-tailed). Source: Authors’ calculation.

7. Discussion of Results

Based on the previous results, a conceptual model can be developed, as illustrated in the following diagram (Scheme 1). The three elements must be balanced and reinforce one another to function effectively. Evaluating both the efficiency and coherence of each element, as well as their combined operation, serves as a measure of successful and efficient organization—particularly in the educational process—yielding positive results in the short, medium, and long term.



Scheme 1. Conceptual model.

Grounded in the research findings and the proposed conceptual model, effective business policies and strategies for managing the educational process can be formulated, aimed at positioning the higher education institution as a leader in its field, delivering top-quality services. This study may inspire the owners and management of higher education institutions to gain new insights into strategic models and approaches for building a successful institution. Key topics for improving management in educational institutions include building leadership teams, fostering a culture of trust, and developing a strong strategic model.

8. Implications of Online Media Sources on the Credibility and Trustworthiness of Information

Media literacy is crucial for managing information in the online environment, which involves the ability to gather, analyze, and, in many cases, redistribute both original and modified media content. Zhang and Jiang [39] correctly identify online media as the primary platforms for disseminating information, highlighting the rise of information disturbances that undermine the credibility and authenticity of public discourse. As the global media landscape has erased spatial and temporal boundaries, addressing the erosion of online information credibility requires a causal approach, including the implementation of clear, unambiguous, and enforceable legal frameworks that respect ethical differences in multicultural, multi-ethnic, and multi-faith contexts.

However, traditional detection methods, such as rule-based systems, metadata analysis, and fact-checking, often fall short when confronted with sophisticated disinformation, including fake profiles and content. This threatens the integrity of information and erodes social trust [40]. A continuous process for distinguishing authentic information from false content must be established at the source, as digital traces cannot be erased or neutralized afterward. This is particularly important for user-generated content, where misinformation often arises not from malicious intent but from a lack of knowledge, skills, or understanding that media discourse cannot be separated from its context.

The integration of virtual reality (VR) and augmented reality (AR) technologies adds another layer of complexity, potentially creating barriers to accessibility and inclusivity, especially for older generations [41].

9. Conclusions

The study's findings indicate that individuals with diverse personality traits develop a range of skills. Character, defined as a set of attributes that shape how a person interacts

with others, behaves, fulfills responsibilities, and adheres to social norms, plays a crucial role. Notably, higher research skill levels were linked to better information management, while increased self-motivation led to enhanced learning, organization, and planning abilities. As a result, students gained more practical, higher-quality knowledge. These elements are comparable to dynamic capabilities, whose effectiveness in ensuring personal applicability depends on external factors.

Educational institutions should place greater emphasis on what happens to students after they graduate, particularly by monitoring graduate employment, job satisfaction, and their navigation of the labor market and broader societal challenges. The competency rankings derived from AHP and FAHP analyses were similar (X21, X11, X22, X12). The most developed competency during this study was the “Ability to manage information”, specifically gathering and analyzing data from various sources. Based on these findings, hypotheses H1 and H2 were confirmed.

Respondents who developed “soft skills” and media literacy during their studies were better equipped to analyze content from social networks, which is essential for decision-making and understanding society. They were also better able to distinguish between authentic information and false content, enabling them to take a more active role in their communities. This confirms hypothesis H3.

This work aims to strengthen and advance future interdisciplinary research by both academics and practitioners while also contributing to the ethical credibility of traditional and digital media, particularly those featuring user-generated content.

Given the changing and dynamic nature of the labor market and the fact that newer generations have higher expectations and are more demanding, companies face the challenge of implementing more effective techniques for attracting and selecting candidates. This also involves creating a strong public image as a desirable employer.

The integration of 21st-century competencies, FAHP, and PCA plays a crucial role in modern decision-making processes. Emphasizing these competencies equips individuals with the skills needed to navigate complex environments, while FAHP and PCA provide robust methodologies for analyzing and making informed decisions based on multifaceted data. Together, they contribute to more effective strategies in education, business, and research, ultimately fostering innovation and adaptability in a dynamic world.

By using FAHP, we can effectively handle the inherent uncertainties and subjectivity in expert judgments. The fuzzy logic aspect allows for a more nuanced representation of opinions, which is crucial in contexts where crisp data is not available or practical. This flexibility enables capturing the complexity of real-world decision-making scenarios more accurately. PCA is instrumental in reducing the dimensionality of data while preserving essential variance, which is vital for improving the interpretability of results. This aspect is particularly beneficial when analyzing large datasets with multiple variables, allowing one to focus on the most significant factors influencing the decision. By identifying key components, PCA enhances the overall analysis by simplifying the dataset without losing critical information. The combination of FAHP and PCA creates a robust framework for decision-making. The use of FAHP and PCA in this research not only provides a rigorous methodological foundation but also contributes to the novelty of the study. By integrating these two approaches, we aim to offer new insights that may not be fully explored using other fuzzy methods. This combination allows for a comprehensive examination of the decision-making process, making it particularly relevant in the context of 21st-century competencies and their implications.

A key drawback of AHP methods, including FAHP, is the presence of incomparable criteria. This issue can be addressed by using the network-like ANP, where all criteria, sub-criteria, and alternatives are organized as nodes within clusters, allowing for comparisons among them when interrelations exist. In this paper, we focus exclusively on the FAHP method, as it allows experts to break down complex problems into a few simplified steps. We have also adapted the model to include five perspectives (points of view) instead of the traditional three. This enables decision-makers to articulate their opinions using descriptive

grades, which can then be further clarified through a mathematical approach. While our proposed method offers insights into various advantages and potentials in the realm of 21st-century competencies, the labor market, and the role of media, it does have limitations. However, these limitations may open avenues for future research. The top-down structure of AHP, which compares criteria across different levels, can result in subcriteria that are difficult to compare. This challenge can be mitigated by using ANP, which accommodates clusters, elements, and interactions within the hierarchical framework. This method can lead to more accurate comparisons of subcriteria. Another limitation is the inability to comprehensively analyze the labor market, including both employees and managers. Drawing on expert experience and judgment, additional criteria or subcriteria could be introduced, facilitating easier employment within human resources, management, media, innovation, and organizational structures of the labor market. Also, trapezoidal, Fermatean, Pythagorean, or Spherical fuzzy numbers could be considered to be applied when FAHP is used, as well as other approaches like TOPSIS, PROMETHEE, and CODAS.

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References

1. Karaca-Atik, A.; Gorgievski, M.J.; Meeuwisse, M.; Smeets, G. Possessing 21st-Century Skills and Building Sustainable Careers: Early-Career Social Sciences Graduates' Perspectives. *Sustainability* **2024**, *16*, 3409. [CrossRef]
2. Van der Heijden, B.I.J.M.; De Vos, A. Sustainable careers: Introductory chapter. In *Handbook of Research on Sustainable Careers*; De Vos, A., Van der Heijden, B.I.J.M., Eds.; Edward Elgar Publishing: Cheltenham, UK, 2015; pp. 1–19.
3. Alghamdi, A.M.; Pileggi, S.F.; Sohaib, O. Social Media Analysis to Enhance Sustainable Knowledge Management: A Concise Literature Review. *Sustainability* **2023**, *15*, 9957. [CrossRef]
4. Salleh, A.M.; Omar, K.; Aburumman, O.J.; Mat, N.H.; Almhairat, M.A. The impact of career planning and career satisfaction on employee's turnover intention. *Entrep. Sustain. Issues* **2020**, *8*, 218–232. [CrossRef]
5. Ananiadou, K.; Claro, M. *21st Century Skills and Competences for New Millennium Learners in OECD Countries*; OECD Education Working Papers, No. 41; OECD Publishing: Paris, France, 2009. Available online: https://www.oecd-ilibrary.org/education/21st-century-skills-and-competences-for-new-millennium-learners-in-oecd-countries_218525261154 (accessed on 1 October 2024).
6. Marlene Scardamalia, M.; Bransford, J.; Kozma, B.; Quellmalz, E. *Tassessment and Teaching of 21st Century Skills, a Report to the Learning and Technology World Forum 2010 in London*. Available online: https://www.researchgate.net/publication/242705214_Assessment_and_Teaching_of_21st_Century_Skills (accessed on 1 October 2024).
7. González-Pérez, L.I.; Ramírez-Montoya, M.S. Components of Education 4.0 in 21st Century Skills Frameworks: Systematic Review. *Sustainability* **2022**, *14*, 1493. [CrossRef]
8. Karakolis, E.; Kapsalis, P.; Skalidakis, S.; Kontzinos, C.; Kokkinakos, P.; Markaki, O.; Askounis, D. Bridging the Gap between Technological Education and Job Market Requirements through Data Analytics and Decision Support Services. *Appl. Sci.* **2022**, *12*, 7139. [CrossRef]
9. Zhu, C.; Liu, X.; Ding, W.; Zhang, S. Cloud model-based multi-stage multi-attribute decision-making method under probabilistic interval-valued hesitant fuzzy environment. *Expert Syst. Appl.* **2024**, *255 Part B*, 124595. [CrossRef]
10. Jiang, J.; Liu, X.; Wang, Z.; Ding, W.; Zhang, S. Large group emergency decision-making with bi-directional trust in social networks: A probabilistic hesitant fuzzy integrated cloud approach. *Inf. Fusion* **2024**, *102*, 102062. [CrossRef]
11. Cáceres-Reche, M.P.; Tallón-Rosales, S.; Ramos Navas-Parejo, M.; De la Cruz-Campos, J.C. Influence of Sociodemographic Factors and Knowledge in Pedagogy on the Labor Market Insertion of Education Science Professionals. *Educ. Sci.* **2022**, *12*, 200. [CrossRef]
12. Jiang, J.; Liu, X.; Wang, Z.; Ding, W.; Zhang, S.; Xu, H. Large group decision-making with a rough integrated asymmetric cloud model under multi-granularity linguistic environment. *Inf. Sci.* **2024**, *678*, 120994. [CrossRef]
13. Perić, G.; Dramićanin, S.; Sančanin, B. Employee satisfaction in hotel industry: The case of hotel Radan in Prolom Banja. *Bizinfo* **2019**, *10*, 25–41. [CrossRef]

14. Goodspeed, T. Untangling the Soft Skills Conversation. Inter-American Dialogue's Education Reports 2016. Available online: <https://www.thedialogue.org/wp-content/uploads/2016/05/Policy-Brief-Soft-Skills-English-FINAL-1.pdf> (accessed on 1 October 2024).
15. Goleman, D. Emotional intelligence. Why it can matter more than IQ. *Learning* **1996**, *24*, 49–50.
16. Penjisević, A.; Sančanin, B.; Simjanović, D.; Randelović, B. The importance of higher education institutions for improving key competencies in the 21st century in the republic of Serbia. *Stud. Teach. Educ.* **2024**, *73*, 203–216. [[CrossRef](#)]
17. Zadeh, L.A. The concept of a linguistic variable and its application to approximate reasoning I. *Inf. Sci.* **1975**, *8*, 199–249. [[CrossRef](#)]
18. Zadeh, L.A. The concept of a linguistic variable and its application to approximate reasoning II. *Inf. Sci.* **1975**, *8*, 301–357. [[CrossRef](#)]
19. Zadeh, L.A. The concept of a linguistic variable and its application to approximate reasoning-III. *Inf. Sci.* **1975**, *9*, 43–80. [[CrossRef](#)]
20. Chou, J.S.; Pham, A.D.; Wang, H. Bidding strategy to support decision-making by integrating fuzzy AHP and regression-based simulation. *Autom. Constr.* **2013**, *35*, 517–527. [[CrossRef](#)]
21. Milošević, D.M.; Milošević, M.R.; Simjanović, D.J. Implementation of Adjusted Fuzzy AHP Method in the Assessment for Reuse of Industrial Buildings. *Mathematics* **2020**, *8*, 1697. [[CrossRef](#)]
22. Kulak, O.; Durmusoglu, B.; Kahraman, C. Fuzzy multi-attribute equipment selection based on information axiom. *J. Mater. Process. Technol.* **2005**, *169*, 337–345. [[CrossRef](#)]
23. Simjanović, D.J.; Zdravković, N.; Vesić, N.O. On the Factors of Successful e-Commerce Platform Design during and after COVID-19 Pandemic Using Extended Fuzzy AHP Method. *Axioms* **2022**, *11*, 105. [[CrossRef](#)]
24. Chang, D.Y. Application of the extent analysis method on fuzzy AHP. *Eur. J. Op. Res.* **1996**, *95*, 649–655. [[CrossRef](#)]
25. Wang, W.M.; Lee, A.H.I.; Chang, D.T. An integrated FA-FEAHP approach on the social indicators of Taiwan's green building. *Glob. Bus. Econ. Rev.* **2009**, *11*, 304–316. [[CrossRef](#)]
26. Kahraman, C.; Cebeci, U.; Ruan, D. Multi-attribute comparison of catering service companies using fuzzy AHP: The case of Turkey. *Int. J. Prod. Econ.* **2004**, *87*, 171–184. [[CrossRef](#)]
27. Domínguez, S.; Carnero, M.C. Fuzzy Multicriteria Modelling of Decision Making in the Renewal of Healthcare Technologies. *Mathematics* **2020**, *8*, 944. [[CrossRef](#)]
28. Janackovic, G.L.; Savic, S.M.; Stankovic, M.S. Selection and ranking of occupational safety indicators based on fuzzy AHP: A case study in road construction companies: Case study. *S. Afr. J. Ind. Eng.* **2013**, *24*, 175–189. [[CrossRef](#)]
29. Ghorui, N.; Ghosh, A.; Algehyne, E.A.; Mondal, S.P.; Saha, A.K. AHP-TOPSIS Inspired Shopping Mall Site Selection Problem with Fuzzy Data. *Mathematics* **2020**, *8*, 1380. [[CrossRef](#)]
30. Chan, F.T.S.; Kumar, N. Global supplier development considering risk factors using fuzzy extended AHP-based approach. *Omega* **2007**, *35*, 417–431. [[CrossRef](#)]
31. Koohathongsumrit, N.; Luangpaiboon, P. An integrated FAHP–ZODP approach for strategic marketing information system project selection. *Manag. Decis. Econ.* **2022**, *43*, 1792–1809. [[CrossRef](#)]
32. Koohathongsumrit, N.; Chankham, W. Risk Analysis of Underground Tunnel Construction with Tunnel Boring Machine by Using Fault Tree Analysis and Fuzzy Analytic Hierarchy Process. *Safety* **2024**, *10*, 68. [[CrossRef](#)]
33. Ayvaz, B.; Tatar, V.; Sağır, Z.; Pamucar, D. An integrated Fine-Kinney risk assessment model utilizing Fermatean fuzzy AHP-WASPAS for occupational hazards in the aquaculture sector. *Process Saf. Environ. Prot.* **2024**, *186*, 232–251. [[CrossRef](#)]
34. Wang, Y.-C.; Chen, T.-C.T. A Partial-Consensus Posterior-Aggregation FAHP Method—Supplier Selection Problem as an Example. *Mathematics* **2019**, *7*, 179. [[CrossRef](#)]
35. Simjanovic, D.; Randelović, B. Criteria Affecting Academic Performance During the COVID-19 Pandemic, Scientific Conference with International Participation. In *Obrazovne Aktivnosti i Vaspitno-Obrazovni Rad u Uslovima Pandemije*; Randjelovic, B., Ed.; Teachers Faculty: Leposavic, Kosova, 2022; pp. 39–40.
36. Ceballos, B.; Lamata, M.T.; Pelta, D.A. A comparative analysis of multi-criteria decision-making methods. *Prog. Artif. Intell.* **2016**, *5*, 315–322. [[CrossRef](#)]
37. Vinogradova-Zinkevič, I.; Podvezko, V.; Zavadskas, E.K. Comparative Assessment of the Stability of AHP and FAHP Methods. *Symmetry* **2021**, *13*, 479. [[CrossRef](#)]
38. Cohen, J.W. *Statistical Power Analysis for the Behavioral Sciences*, 2nd ed.; Lawrence Erlbaum Associates: Hillsdale, NJ, USA, 1988.
39. Zhang, H.; Jiang, L. Applying the Constructive Journalism Approach to Combat Chinese Information Disorder in the Digital Age. *J. Media* **2024**, *5*, 1526–1538. [[CrossRef](#)]
40. Papageorgiou, E.; Chronis, C.; Varlamis, I.; Himeur, Y. A Survey on the Use of Large Language Models (LLMs) in Fake News. *Future Internet* **2024**, *16*, 298. [[CrossRef](#)]
41. Eskiadi, I.G.; Panagiotou, N. Embracing Immersive Journalism: Adoption and Integration by News Media Producers. *J. Media* **2024**, *5*, 1494–1508. [[CrossRef](#)]

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