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Coding Program Selection using Spherical Fuzzy Analytic Hierarchy and Pythagorean Fuzzy Analytic Hierarchy Processes

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Abstract

Today, coding is not a field that belongs only to software developers; it has become a field of interest to many people from different professions. The coding education designed for elementary school level resulting from the changes made in the curriculum has led to teaching analytical thinking to children. Deciding the most suitable software for children among all the options is an important issue. This paper aims to extend the classical Analytical Hierarchy Process (AHP) and look at the spherical fuzzy analytical hierarchy (SF-AHP) method to show its applicability to the problems of coding software program selection for children through a comparative analysis using Pythagorean AHP (PF-AHP). After performing the analysis by using the proposed method, it was found that technological facilities, diversity, cost and environmental conditions were the most critical factors according to SF-AHP and PF-AHP methodologies. According to these criteria, the educational programming platform 'Tynker' was determined to be the best alternative using both these methods.

Keywords: Multi Criteria Decision Making, AHP, Spherical Fuzzy-AHP, Pythagorean Fuzzy-AHP

1. INTRODUCTION

AHP is one of the most preferred multi-criteria decision-making methods. The hierarchical order in this method was developed by Saaty [1]. The purpose of the decision making is located at the highest level. The main criteria and sub criteria – if any – under the main criteria are located one level lower. Below that there are decision options, namely alternatives. AHP can be easily applied with many criteria and is a very effective method in making group decisions. The flexibility of the result can be easily tested thanks to sensitivity analysis. AHP can make both quantitative and qualitative criteria evaluations in decision making. It can involve the preferences, judgments, intuition and experiences of the group or individual in the decision process. It is one of the most useful multi-criteria, decision-making methods enabling complex problems to be solved using a hierarchical structure.

The decision-making process is a complex process as it involves many different factors. In this process, preferences, intuition, experiences, judgments, opinions, and objective or subjective evaluations can make decision-making more difficult. Therefore, classical logic may be insufficient for decision making. Also, since the human mind is quite complex in terms of mentality and decision making, an approach different from classical logic is required in this process. There is a 'true' or 'false' state in the classical logic system. In this system, it is thought that a third possibility is impossible to realize and such situations are usually called paradoxes. Classical logic has the two values (0, 1), while fuzzy logic has values in the range [0, 1]. The main idea of fuzzy logic is that a proposition can be 'true', 'false', 'very true', 'very false', 'approximately true' or 'approximately false'. In other words, truth is a function that relates values in a set containing infinite numbers of truth values between the classical 'true' and 'false' or numerically to a range of real numbers [0, 1]. This statement is accepted as a result of Zadeh's [2] first work on fuzzy logic. Although the classical fuzzy set theory developed by Zadeh works well to overcome the shortcomings experienced by the decision maker in decision making, the complexity of human decisions and the diversity of linguistic expressions have led researchers to seek other approaches in this area. Therefore, Torra [3] defined multi-fuzzy sets, in other words, fuzzy sets with more than one membership. Then, Rodriguez et al. [4] conducted a series of studies to examine these sets and to enrich the content of linguistic expressions. Thus, it was made possible to use richer expressions in a more flexible and impressive way when comparing two alternatives. Over the years, many studies have been carried out in this area and the studies have made significant contributions to published literature. Studies on fuzzy sets are shown in Figure 1 [5].

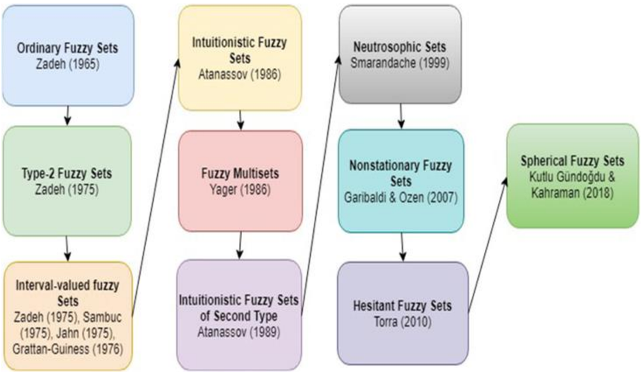

Figure 1. Extensions of Fuzzy Sets

In this study, a decision-making model based on spherical fuzzy sets was developed for the selection of applications to teach children coding. This selection problem involves uncertainty. Coding education, which has been included to start in the elementary school curriculum, gives children an edge in their analytical thinking, creativity and problem-solving skills, as well as success in computer science. Studies have shown that children who learn coding can create more practical solutions to the problems they encounter, and they are better at evaluating the results. Coding education also has a structure that sets goals for success and makes it intriguing for children who achieve these goals step by step. In recent years, developments in the area of coding has led to diversity in user profiles. Platforms have been created for children in the field of coding, and fun and instructive software has been designed to appeal to their level. However, the fact that each software program has different features makes it difficult to choose an appropriate environment for children. It is necessary to determine the objectives of using the software in coding education and to choose the appropriate software program accordingly. Comparison and selection of these software programs is very important and requires the utmost diligence. Educational software should be suitable for the development of the child in a way that they can make progress according to their own pace and knowledge levels. Choosing the right coding software is also very important in terms of contributing to the learning of students who will use the software, achieving the teaching goals, keeping the students' attention focused and boosting their motivation.
In this research, case study included four criteria, three sub criteria under each criterion, and four alternatives were presented. This decision model integrated the analytic hierarchy process (AHP) with spherical fuzzy sets. The difference in this study is that, for the first time, SF-AHP was used to choose from among the platforms that teach coding to children. In addition, the results in this study were cross-checked using the Pythagorean fuzzy AHP method, and the two methods were compared to overcome uncertainty and achieve optimum results. SF-AHP enables decision makers to independently reflect their uncertainty in the decision process by using a linguistic evaluation scale based on spherical fuzzy sets. Following the introduction in Part 1 which summarizes a literature review on fuzzy AHP, this study consists of the following sections: Part 2 includes the proposed multi-criteria decision-making (MCDM) technique and the spherical fuzzy AHP method (SF-AHP). Part 3 applies the SF-AHP method to the problem of selecting a platform to teach coding to children and it includes the comparative analysis of SF-AHP and Pythagorean Fuzzy Analytic Hierarchy Processes (PFAHP), and finally, conclusions are drawn on the findings and some evaluations are made in Part 4.

The notion that 'Everything is a ranking problem' forms the basis for fuzzy logic. In other words, fuzzy logic deals with the degree of occurrence of events rather than with the probability of occurrence. Fuzzy logic uses linguistic variables such as 'cold', 'warm', 'few', 'very few', similar to when one person is talking to another or explaining something. Fuzzy logic can be called the real-life application of mathematics [6]. A fuzzy set is a class of objects that has a continuity of membership degrees. Such a set is characterized by a membership function that assigns a membership degree ranging from zero to one for each object. Fuzzy sets and fuzzy logic are powerful mathematical tools for modeling commonsense reasoning in the decision-making process without complete and precise knowledge of uncertain systems in industry, nature and humanity. Their role is important when applied to complex phenomena that cannot be easily described by traditional mathematical methods, especially when the goal is to find a good approximate solution [7].

Providing a broader framework than classical set theory, fuzzy set theory contributes to the ability to reflect the real world [8]. Modeling using fuzzy sets has proven to be an effective way to formulate decision-making problems when available information is subjective and uncertain [9]. With the increase of type-2 fuzzy logic studies since the late 1990s, fuzzy logic theory, which has been used in fuzzy logic applications up to the current time, is now regarded as type-1 fuzzy logic for the first time in published literature [10]. Fuzzy logic theory is based on computation with fuzzy sets, which is an extension of classical sets called 'sharp sets' in the context of fuzzy logic. In classical set theory, in those cases where each object may or may not be an element of a particular set, the membership of each object in a particular set is determined by a degree, called 'membership degree'. In type-1 fuzzy sets, the membership degree is defined by a definite number within the interval [0,1], whereas in type-2 fuzzy sets, the membership degree is fuzzy in itself and is generally considered to be a secondary membership function. If the secondary membership function is – at most – 1 at each point, it has a type-2 set range. Thus, type-2 fuzzy sets contain a third dimension and an area occupied by some uncertainty, and it provides an extra degree of freedom to overcome those uncertainties. Type-2 fuzzy logic, a new expansion of fuzzy logic, can model uncertainties and reduce their effect due to the fuzzy membership function and its third dimension. When the uncertainties disappear, type-2 fuzzy logic can be reduced to type-1 fuzzy logic.

The concept of a type-2 fuzzy set was introduced by Zadeh as an extension of an ordinary fuzzy set (type-1 fuzzy set). These sets are fuzzy sets whose membership degrees are themselves type-1 fuzzy sets; they are very useful in situations where it is difficult to determine the full membership function for a fuzzy set. Therefore, they are useful in including uncertainty [11]. After Zadeh's (1965) pioneering work, fuzzy set theory has been expanded in several directions [12]. Recently, based on expanded forms of the fuzzy set, Torra proposed a new generalized fuzzy set called the hesitant fuzzy set (HFS), which provides new perspectives for further research on decision making in uncertain environments [13]. HFS provides many advantages compared to the traditional indefinite set and its other extensions, especially in group decision making with anonymity [14]. Torra also defined the complement, union and intersection of HFSs. Torra and Narukawa (2009) presented an extension principle allowing existing operations on fuzzy sets to be generalized to HFSs and described the implementation of this new set in the decision-making framework. Since the possible values of membership degrees in an HFS are random, the HFS is somewhat more natural than any other expansion of the fuzzy set as regards uncertainty and its representation. It should be noted that modeling fuzzy information with other forms of expanded fuzzy sets is based on obtaining single or range values that should include and express the information provided by decision makers (or experts) when determining the membership of an object to another object [15]. As Yu (1973) points out, "When a group of individuals plan to form a company with themselves as shareholders or form a union to increase their total bargaining power, they often find some disagreement among themselves. Conflicts are different from subjective evaluations of emerging decision-making problems". Since decision makers (or experts) could have different views on alternatives due to their different knowledge or experience, and cannot easily convince each other, it can sometimes be difficult to get a consensus, but there are several possible assessment values. HFS is suitable for solving this problem and is more powerful than any other extended fuzzy set [16]. In intuitionistic fuzzy sets (IFS), the computational complexity is greater because two types of uncertainties are involved. However, when better results are desirable, especially in the diagnosis of medical images where uncertainty is high, it becomes easier to obtain accurate results. Therefore, researchers try to use it in real-time practices [17].

While Zadeh's fuzzy set theory was modeled to show only the degree of membership defined in the range of [0,1], Atanassov's intuitionistic fuzzy set theory also defined the degree of non-membership in addition to the membership degree. In the intuitionistic fuzzy set theory, both membership and non-membership degrees are in the range [0,1]. Looking from this point of view, the sum of membership and non-membership degrees in traditional fuzzy set theory is calculated to be 1. However, the sum of these two parameters need not be 1 in intuitionistic fuzzy set theory. The intuitionistic fuzzy set is a powerful tool in case of uncertainty. A prominent feature of the intuitionistic fuzzy set is that it assigns a membership degree and a non-membership degree to each element, and therefore it constitutes an extension of Zadeh's fuzzy set, which assigns only one membership degree to each element. When published literature was examined, studies related to the method in question included Bustince et al. who defined some intuitionistic fuzzy generators and investigated the presence of equilibrium points and binary points, Szmidt and Kacprzyk's study of an unlikely type of entropy measurement for A-IFSs, Mondal and Samantaîn's introduction of the concept of intuitionistic openness grading on fuzzy subsets of a non-empty set and studies for intuitionistic fuzzy topological field definition [18]. In addition, Deschrijver and Kerre established the relationships between A-IFS fuzzy sets, range-valued fuzzy sets and range-valued A-IFSs, while Bustince and Burillo, and Deschrijver and Kerre, investigated the composition of intuitionistic fuzzy relationships. Dudek et al. considered the intuitionistic fuzziness of the concept of sub-hyper quasigroups in a hyper quasigroup and explored some properties of such sub-hyper quasigroups.

In the decision-making process, decision makers can make their own assessment of each of the alternatives. Some factors that affect decision makers in an uncertain environment cause them to be unable to determine exact values. Fuzzy logic is applied to deal with those uncertainties. The Pythagorean fuzzy set is built on two basic functions. These are membership and non-membership functions. Pythagorean fuzzy set logic is more concerned with the uncertainty of these two basic functions. It helps to model the uncertainties and subjective statements of decision makers in the best way [19]. The Pythagorean fuzzy set generalized by Yager is a new tool for overcoming uncertainty given the degree of membership μ meeting the condition μ2 + ν2≤1 and the non-membership value ν. Pythagoras fuzzy sets (PFS) are an effective generalization of the intuitionistic fuzzy set with a membership value and the square sum of these values is less than or equal to 1 [20]. AHP is a powerful and flexible MCDM tool that constructs a complex decision-making problem hierarchically at several different levels considering both qualitative and quantitative features [21]. AHP combines both subjective and objective evaluations in a holistic framework based on ratio scales in simple pairwise comparisons and helps the analyst to organize critical aspects of a problem in a hierarchical structure. MCDM can measure the consistency of the decisions of a decision-maker. Instead of measuring weights, two-way comparisons allow weights of criteria and alternative scores to be derived from comparison matrices. AHP helps decision-makers organize the criteria and sub criteria of a problem in a hierarchical structure similar to a family tree [22]. In the classical method, the evaluations of decision makers are represented as definite numbers. Nevertheless, fuzzy logic provides a mathematical capability that can be used to capture the uncertainties accompanying the human cognitive process in cases where decision makers cannot express their evaluations with definite numbers [23]. Therefore, the original AHP method has been extended to several fuzzy versions with the aim of improvements in spite of missing information and uncertainties.

2. MATERIALS AND METHODS

The proposed spherical fuzzy AHP method in this study consists of several steps described in the following section. The flow chart for the method used in Figure 2 (in part 3) is shown to clearly illustrate the principles of the study.

- Step 1. A hierarchical structure is created.
- Step 2. Two-way comparisons are constructed using spherical fuzzy judgment matrices based on the linguistic terms given in Table 1. Equations (1) and (2) are used to obtain the score indices (SI) in Table 1.

Table 1. Linguistic measures of importance

Linguistic measures of importance used for pairwise comparisons		
	(μ, υ, π)	Score Index (SI)
Absolutely more important (AMI)	(0.9, 0.1, 0.0)	9
Very high importance (VHI)	(0.8, 0.2, 0.1)	7
High importance (HI)	(0.7, 0.3, 0.2)	5
Slightly more important (SMI)	(0.6, 0.4, 0.3)	3
Equally important (EI)	(0.5, 0.4, 0.4)	1
Slightly low importance (SLI)	(0.4, 0.6, 0.3)	1/3
Low importance (LI)	(0.3, 0.7, 0.2)	1/5
Very low importance (VLI)	(0.2, 0.8, 0.1)	1/7
Absolutely low importance (ALI)	(0.1, 0.9, 0.0)	1/9

$$SI = \sqrt{\left|100 * \left[(\mu_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2 - (\upsilon_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2\right]\right|}$$

for AMI, VHI, HI, SMI, and EI (1)

$$\frac{1}{SI} = \frac{1}{\sqrt{\left|100 * \left[(\mu_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2 - (\upsilon_{\tilde{A}_s} - \pi_{\tilde{A}_s})^2\right]\right|}}$$

for EI, SLI, LI, VLI and ALI (2)

- Step 3. The consistency of pairwise comparison matrices is checked.
- Step 4. The spherical fuzzy local weights for criteria and alternatives are calculated.

Using the SWAM operator given in Equation (3), the weight of each alternative is then determined.

$$SWAM_w(A_{SI}, \ldots, A_{Sn}) = \left\langle \left[1 - \prod_{i=1}^{n}(1 - \mu_{A_{si}}^2)^{wi}\right]^{\frac{1}{2}}, \prod_{i=1}^{n}(\upsilon_{A_{si}}^{wi}), \left[\prod_{i=1}^{n}(1 - \mu_{A_{si}}^2)^{wi} - \prod_{i=1}^{n}(1 - \mu_{A_{si}}^2 - \pi_{A_{si}}^2)^{wi}\right]^{\frac{1}{2}} \right\rangle$$

where $w = 1/n$. (3)

- Step 5. A hierarchical ranking of layers is created to obtain overall weights.

Criterion weights are made fuzzy using equation (4) and the score function (S).
It is normalized by equation (5).
The spherical fuzzy product given by Eq. (6) is applied.

$$S(\tilde{w}_j^s) = \sqrt{\left|100 * \left[(3\mu_{\bar{A}_s} - \frac{\pi_{\bar{A}_s}}{2})^2 - (\frac{\upsilon_{\bar{A}_s}}{2} - \pi_{\bar{A}_s})^2\right]\right|} \quad (4)$$

$$\bar{w}_j^s = \frac{S(\tilde{w}_j^s)}{\sum_{j=1}^{n} S(\tilde{w}_j^s)} \quad (5)$$

$$\tilde{A}_{sij} = \bar{w}_j^s . \tilde{A}_{s_i} = \left\langle \left(1 - (1 - \mu_{\tilde{A}_s}^2)^{\bar{w}_j^s}\right), \upsilon_{\tilde{A}_s}^{\bar{w}_j^s}, \left((1 - \mu_{\tilde{A}_s}^2)^{\bar{w}_j^s} - (1 - \mu_{\tilde{A}_s}^2 - \pi_{\tilde{A}_s}{}^2)^{\bar{w}_j^s}\right)^{\frac{1}{2}} \right\rangle \quad \forall i \quad (6)$$

The final spherical fuzzy AHP score ($\tilde{F}$), for each alternative A_i, is obtained by carrying out the spherical fuzzy arithmetic addition over each global preference weights, as given in Eq. (7)

$$\tilde{F} = \sum_{J=1}^{n} \tilde{A}_{S_{ij}} = \tilde{A}_{S_{i1}} \oplus \tilde{A}_{S_{i2}} \ldots \oplus \tilde{A}_{S_{in}} \quad \forall i \quad (7)$$

i.e. $\tilde{A}_{S_{11}} \oplus \tilde{A}_{S_{12}} =$

$$\left\langle (\mu_{\tilde{A}_{S_{11}}}^2 + \mu_{\tilde{A}_{S_{12}}}^2 - \mu_{\tilde{A}_{S_{11}}}^2 \mu_{\tilde{A}_{S_{12}}}^2)^{1/2}, \upsilon_{\bar{A}_{S_{11}}} \upsilon_{\bar{A}_{S_{12}}}, \left((1 - \mu_{\tilde{A}_{S_{12}}}^2)\pi_{\tilde{A}_{S_{11}}}^2 + (1 - \mu_{\tilde{A}_{S_{11}}}^2)\pi_{\tilde{A}_{S_{12}}}^2 - \mu_{\tilde{A}_{S_{11}}}^2 \mu_{\tilde{A}_{S_{12}}}^2\right)^{1/2} \right\rangle$$

- Step 6. The final score for each alternative is determined using the score function given by Eq. (4).
- Step 7. Alternatives are ranked according to their point scores. The largest value indicates the best solution [24].

3. FINDINGS

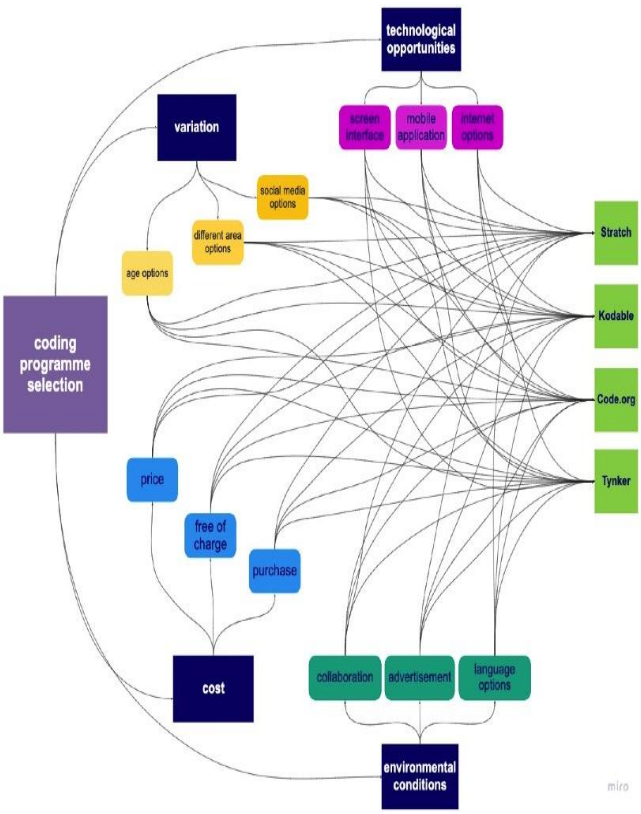

Figure 2. Hierarchical structure for the main and sub criteria

Two-way comparisons are constructed using spherical fuzzy judgment matrices and results are given below. Pairwise comparison of main criteria is given in Table 2.

This study was conducted to compare and select a software program to be used to educate children in coding. A comparison and selection of this software is very important and should be done diligently. Four main criteria and 12 sub-criteria are investigated in the study. The main criteria were determined to be C1: Technology, C2: Diversity, C3: Price and C4: Environmental Factors. Figure 2 shows the hierarchical structure showing the main criteria and sub criteria. The main and sub criteria were evaluated according to the linguistic terms given in Table 1 by the decision-making expert group. Pairwise comparison matrices were calculated according to the corresponding numerical values in the classical AHP method for the linguistic scale given in Table 1. Paired comparisons and the spherical weights obtained are given in Tables 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17 and 18. Table 19 shows the weights of the alternatives according to the spherical fuzzy evaluation. The ranking of the alternatives compared is given in Table 20.

Table 2. Pairwise comparison of main criteria

Criteria		w^s		w
C1	0.77	0.22	0.18	0.37
C2	0.56	0.43	0.29	0.25
C3	0.50	0.49	0.28	0.23
C4	0.34	0.65	0.26	0.15

Using Eq. (4), w^s scores were obtained and the results are given below.

Table 3. Pairwise comparison caused by technological opportunities

C1		w^s		w
C11	0.49	0.48	0.32	0.30
C12	0.39	0.58	0.31	0.24
C13	0.70	0.29	0.24	0.46

Table 4. Pairwise comparison caused by variation

C2		w^s		w
C21	0.71	0.29	0.23	0.43
C22	0.67	0.32	0.27	0.39
C23	0.33	0.66	0.27	0.18

Table 5. Pairwise comparison caused by cost

C3		w^s		w
C31	0.79	0.20	0.18	0.49
C32	0.35	0.63	0.28	0.20
C33	0.53	0.46	0.27	0.31

Table 6. Pairwise comparison caused by environmental conditions

C4		w^s		w
C41	0.38	0.60	0.31	0.22
C42	0.48	0.50	0.31	0.28
C43	0.79	0.20	0.18	0.50

Table 7. Pairwise comparison of alternatives caused by ease of display screen interface

C11		w^s		w
A1	0.67	0.31	0.25	0.32
A2	0.50	0.49	0.27	0.23
A3	0.35	0.63	0.27	0.16
A4	0.60	0.38	0.28	0.29

Table 8. Pairwise comparison of alternatives caused by use of mobile application

C12		w^s		w
A1	0.77	0.22	0.18	0.37
A2	0.64	0.36	0.24	0.29
A3	0.44	0.55	0.29	0.19
A4	0.35	0.64	0.28	0.15

Table 9. Pairwise comparison of alternatives caused by use offline

C13		w^s		w
A1	0.57	0.41	0.30	0.28
A2	0.49	0.49	0.33	0.23
A3	0.61	0.37	0.30	0.30
A4	0.39	0.59	0.30	0.18

Table 10. Pairwise comparison of alternatives caused by age options

C21		w^s		w
A1	0.43	0.54	0.33	0.20
A2	0.54	0.44	0.33	0.26
A3	0.55	0.40	0.35	0.27
A4	0.55	0.40	0.35	0.27

Table 11. Pairwise comparison of alternatives caused by different area options

C22		w^s		w
A1	0.65	0.35	0.25	0.30
A2	0.49	0.51	0.26	0.22
A3	0.71	0.28	0,.23	0.33
A4	0.33	0.65	0.26	0.14

Table 12. Pairwise comparison of alternatives caused by use of social media options

C23		w^s		w
A1	0.44	0.51	0.35	0.21
A2	0.64	0.35	0.28	0.32
A3	0.44	0.51	0.35	0.21
A4	0.54	0.44	0.33	0.26

Table 13. Pairwise comparison of alternatives caused by price

C31		w^s		w
A1	0.39	0.57	0.32	0.17
A2	0.68	0.31	0.23	0.32
A3	0.39	0.57	0.32	0.17
A4	0.71	0.28	0.23	0.34

Table 14. Pairwise comparison of alternatives caused by being free of charge

C32		w^s		w
A1	0.69	0.28	0.26	0.33
A2	0.43	0.57	0.28	0.19
A3	0.69	0.28	0.26	0.33
A4	0.36	0.63	0.28	0.16

Table 15. Pairwise comparison of alternatives caused by opportunity to purchase

C33		w^s		w
A1	0.75	0.24	0.23	0.33
A2	0.31	0.69	0.25	0.13
A3	0.75	0.24	0.23	0.33
A4	0.48	0.53	0.25	0.21

Table 16. Pairwise comparison of alternatives caused by collaboration

C41		w^s		w
A1	0.65	0.35	0.25	0.30
A2	0.35	0.64	0.28	0.15
A3	0.76	0.24	0.21	0.36
A4	0.44	0.55	0.29	0.19

Table 17. Pairwise comparison of alternatives caused by advertisement

C42		w^s		w
A1	0.76	0.24	0.21	0.35
A2	0.32	0.67	0.25	0.14
A3	0. 65	0.35	0.25	0.30
A4	0.48	0.52	0.26	0.22

Table 18. Pairwise comparison of alternatives caused by language options

C43		w^s		w
A1	0.75	0.24	0.23	0.35
A2	0.37	0.61	0.30	0.16
A3	0.66	0.31	0.28	0.30
A4	0.42	0.58	0.28	0.19

Spherical fuzzy weight matrix based on fuzzy approach is given in Table 19.

Table 19. Spherical fuzzy weight matrix based on fuzzy approach

	C11	C12	C13	C14	C21	C22	C23	C24	C31	C32	C33	C34
	0.26	0.19	0.13	0.23	0.20	0.15	0.11	0.18	0.36	0.27	0.19	0.32
A1	0.58	0.67	0.75	0.61	0.65	0.72	0.79	0.68	0.46	0.58	0.69	0.51
	0.38	0.37	0.34	0.39	0.37	0.35	0.32	0.37	0.35	0.35	0.33	0.36
	0.19	0.14	0.10	0.17	0.15	0.11	0.08	0.13	0.26	0.19	0.14	0.23
A2	0.66	0.72	0.79	0.68	0.71	0.77	0.82	0.73	0.57	0.66	0.74	0.60
	0.40	0.38	0.35	0.40	0.38	0.36	0.33	0.37	0.38	0.37	0.34	0.39
	0.17	0.12	0.09	0.15	0.13	0.10	0.07	0.12	0.24	0.18	0.12	0.21
A3	0.69	0.75	0.80	0.71	0.74	0.78	0.83	0.75	0.61	0.69	0.76	0.64
	0.38	0.36	0.33	0.38	0.36	0.34	0.32	0.36	0.37	0.36	0.33	0.37
	0.11	0.08	0.06	0.10	0.09	0.07	0.05	0.08	0.16	0.12	0.08	0.14
A4	0.77	0.81	0.86	0.79	0.81	0.84	0.88	0.82	0.72	0.77	0.82	0.74
	0.34	0.32	0.30	0.34	0.32	0.31	0.28	0.32	0.34	0.32	0.30	0.34

Score values and ranking obtained from SF-AHP approach is given in Table 20.

Table 20. Score values and ranking obtained from SF-AHP Approach

Alternatives	Score Value	Ranking
A1	28.13	4
A2	28.73	3
A3	28.91	2
A4	29.42	1

Tepe et al. (2020) suggested a fuzzy-based risk assessment model to evaluate hazards in a real-case study using PFAHP. Pythagorean AHP and Neutrosophic AHP were successfully proposed in their work. In this study, the proposed methodology was compared with PF-AHP for the coding program selection. Table 21 presents the Pythagorean linguistic scale, which was used for the comparison purpose.

Table 21. Weighting scale for the PF-AHP method [25]

Linguistic terms	PFN equivalents			
	IVPF numbers			
	μ_L	μ_U	V_L	V_U
Certainly Low Importance - CLI	0	0	0.9	1
Very Low Importance - VLI	0.1	0.2	0.8	0.9
Low Importance - LI	0.2	0.35	0.65	0.8
Below Average Importance - BAI	0.35	0.45	0.55	0.65
Average Importance - AI	0.45	0.55	0.45	0.55
Above Average Importance - AAI	0.55	0.65	0.35	0.45
High Importance - HI	0.65	0.8	0.2	0.35
Very High Importance - VHI	0.8	0.9	0.1	0.2
Certainly High Importance - CHI	0.9	1	0	0
Exactly Equal - EE	0.197	0.197	0.197	0.197

The results obtained according to the PF-AHP method are given in Table 22. According to the results obtained from this method, alternative A4 is in first place.

Table 22. Score values and ranking obtained from the PF-AHP approach

Alternatives	Score Value	Ranking
A1	0.118	2
A2	0.116	3
A3	0.100	4
A4	0.148	1

According to the SF-AHP method, the ranking was A4, A3, A2, A1, and according to the PF-AHP method, it was A4, A1, A2, A3. The coding program named Tynker – represented by A4 – is in first place in both methods. The main reason for the difference in rankings is the different assumptions for the two theories. The comparison of the rankings according to both methods is given in Table 23.

Table 23. Comparative ranking values

Alternatives	SF-AHP Ranking	PF-AHP Ranking
A4	1	1
A3	2	4
A2	3	3
A1	4	2

4. DISCUSSION AND CONCLUSION

Children will be able to make better use of their problem-solving skills on issues they will encounter throughout their educational life thanks to the coding knowledge they learn at an early age. Coding software programs designed according to the developmental levels of children aim their presentation to children by using motivational methods that operate through play instead of teaching coding directly. Today, experts are trying to design coding software in a way that is less complex and can be enjoyed by children. There are many parameters to be considered in these studies. In this study, treating the problem as Multi-Criteria Decision Making allows more accurate decisions to be made, as it includes many dimensions simultaneously.

Ease of user interface, availability of a mobile application, availability of the program when it is offline, choosing designs suitable for the age levels of the children, as well as many other criteria such as the program’s pay/free/purchase options or language options are the topics that software developers should consider. The aforementioned criteria – and more – have been generated from the problems and experiences encountered in coding program selection for children. In this study, these parameters were determined as the main criteria and sub-criteria, and leading brands in the sector were compared according to these criteria.

In the study, the problem of coding program selection for children was successfully solved with SF-AHP and compared by PF-AHP cross-checking. Addressing the problem as SF and PF allows for more precise and more flexible assessments. In addition, in this way, human subjective evaluations can be easily adapted to the process.

Some differences were observed in the rankings due to the different assumptions between both methods and the linguistic scales they used. The use of fuzzy logic in this study eased the evaluation process, which is difficult for decision makers because of the differences in coding program selection criteria and measurements. The educational programming platform ‘Tynker’ was determined to be the best alternative using both these methods.

In future studies, SF-AHP can be compared with other multi-criteria decision-making extensions, such as intuitionistic fuzzy or hesitant fuzzy sets. In addition, the methodology suggested can be used in evaluation processes for different problems and its robustness can also be tested for different decision-making problems.

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