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Comparison of AHP and SAW Methods for Predicting Career Interests of SMAN 1 Karanganyar Demak Students

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Abstract

This study compares the efficacy of the Analytic Hierarchy Process (AHP) and Simple Additive Weighting (SAW) methods in predicting career interests of students at SMAN 1 Karanganyar Demak. The research assesses seven key factors: familial influence, educational engagement, individual capabilities, academic performance, institutional resources, resilience of a career, and academic interests. Results show that AHP prioritizes familial influence (28.94%), individual capabilities (17.10%), and educational engagement (16.23%), while SAW highlights career (15.75%), educational engagement (15.61%), and individual capabilities (14.92%). Both methods achieved an accuracy of 83.02%. Career recommendations were categorized into guidance-intensive cases (AHP: 42.68%; SAW: 46.00%), employment-oriented individuals (AHP: 33.96%; SAW: 32.97%), higher education aspirants (AHP: 12.94%; SAW: 10.06%), and entrepreneurial prospects (AHP: 10.42%; SAW: 10.96%).

Keywords: AHP, Career Interest Prediction, MADM, Student Academic Potential, SAW

1 Introduction

Modern education has gone beyond conventional teaching methods, focusing on an individual development approach to identify student capability at SMAN 1 Karanganyar Demak, the complexity of factors influencing career choices requires teachers to accurately recognize and encourage students' Career Interests. Traditional evaluation systems frequently prove inadequate in capturing the intricate aspects of student capacity, underscoring the necessity for advanced, evidence-based analytical methodologies.

Recent academic investigations have revealed significant limitations in addressing career guidance challenges. Kusumawardhany et al. explored the implementation of Analytical Hierarchy Process (AHP) and Profile Matching techniques for determining student majors at SMA Negeri 5 Tangerang Selatan [1]. While their research demonstrated promising results in reducing decision-making subjectivity, it primarily concentrated on academic metrics, overlooking crucial professional longevity factors. Similarly, Nurhanijah et al. investigated Simple Additive Weighting (SAW) applications in student tracking systems, yet their approach lacked integration with comprehensive career guidance frameworks. Despite these individual methodological advances, there remains a notable absence of comparative analyses between AHP and SAW methodologies in predicting career interests [2].

At SMAN 1 Karanganyar Demak, with its substantial student population of 1,113, the existing career guidance framework presents several critical limitations. The current system lacks the capability to objectively evaluate multiple criteria simultaneously, failing to incorporate essential factors such as family influence, academic achievement, and career resilience considerations. This situation necessitates the development of a more systematic and quantifiable approach to career recommendations [3].

To address these challenges, this research pursues three primary objectives. First, it aims to conduct a comparative analysis of AHP and SAW methodologies' effectiveness in predicting student career interests. Second, it seeks to identify and evaluate the crucial factors that influence students'

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career decisions through both analytical frameworks. Third, it strives to develop an enhanced career recommendation model based on the comparative analysis of these methodologies.

The significance of this investigation extends beyond theoretical contributions to practical applications in educational guidance systems. By examining seven fundamental factors family dynamics, learning engagement, student aptitude, academic performance, institutional resources, occupational continuity, and academic interests this research establishes a comprehensive framework for career guidance. Furthermore, this study's findings offer valuable insights for implementing data-driven career guidance systems in secondary education institutions, potentially transforming how schools approach career counseling and student development.

This research's distinctive contribution lies in its systematic comparison of AHP and SAW methodologies within the context of career interest prediction. Through empirical analysis and methodological innovation, this study aims to enhance the precision and effectiveness of career guidance systems while establishing a robust foundation for future research in educational decision support systems. The integration of multiple evaluation criteria and sophisticated analytical methods represents a significant advancement in addressing the complex challenges of career guidance in secondary education.

2 Literature Review

Differentiated learning strategy plays a key role in education, particularly in supporting students' career predictions. Maulidia and Prafitasari explain that a varied learning approach can increase student motivation and learning outcomes [4]. Sutrisno explain in addition, differentiated learning is not only effective in enhancing student independence but also prepares them to plan their careers [5]. Kasan and Ibrahim highlight the importance of understanding students' talents and interests, with 75.68% of students showing a high internal factor in their career planning [6]. Lindawati noted that good communication between students and parents, teachers, and peers has a positive influence on students' career maturity, which is reflected in the moderate category on the average value of career maturity [7]. Finally, research by Lv and Gong shows that the application of the MADM method can help students determine career choices that match their potential. Thus, the integration of these various approaches in education can encourage students to be better prepared to face career challenges in the future [8].

Quality education has a significant impact on the career maturity of students, especially through the application of innovative curricula. Research by Hutabarat shows that the implementation of the Merdeka Belajar Curriculum at SMA Negeri Padangsidimpuan reached an average of 84.11%, indicating that the implementation was good [9]. Arianne and Purwanti found that 28.9% of grade X students have a high career maturity level, although many of them still feel uncertain in planning for the future [10]. Kabassi emphasizes the importance of using multi-criteria decision-making methods such as PROMETHEE to evaluate educational programs, which can help students determine the right career path [11]. In addition, Alwendi revealed that decision support systems can enhance objectivity in assessments that contribute to the improvement of education quality [12]. Akram also highlighted how the ELECTRE method can be used to assist in better decision-making in the context of education. Thus, the application of appropriate evaluation methods in education is crucial to enhance students' readiness in planning their careers, which can reduce confusion and increase their confidence in choosing the right career path [13].

Education plays a crucial role in developing students' potential, especially in aspects of achievement related to career planning. Meanwhile, Putri Fatimah applied the PROMETHEE method to evaluate student performance, involving 70 alternative data with various criteria, including final grades and skills [14]. Emphasizing that an effective decision support system in teacher performance assessment can contribute to the improvement of education quality and support student career (Pramana et al., 2022). In addition, Lowell and Atmojo showed that the PROMETHEE method can help reduce subjectivity in the selection of student organization members, which can be adapted to improve career decisions [15]. Khotimah added that the combination of AHP and SAW methods in selecting the best teachers can provide more effective recommendations for students in planning their career paths [16].

In the development of technology-based decision support systems, research shows that the application of methods such as Analytical Hierarchy Process (AHP) and Simple Additive Weighting

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(SAW) can enhance the effectiveness of student evaluation [17]. Research by Esmaeilishirazifard et al. reveals that water-saving strategies implemented by households can be analyzed using an MCDM approach, which is also relevant in the context of student career predictions. Quantitative data shows that 40% of students prefer simple saving methods, reflecting their tendency to choose practical solutions [18]. The research by Ziemba also found that 83% of students felt more motivated when using an interactive e-learning platform, which contributed to improved learning outcomes [19]. Therefore, the application of MCDM methods in education not only improves the evaluation process but also provides better insights in decision-making related to student careers [20].

Previous research shows the diversity of the application of AHP and SAW methods in decision support systems. Siddiq and Wirani used both methods to determine outstanding lecturers, while Rojakul applied them in the assessment of cooperative credit allocation [21]. Both studies reveal the effectiveness of AHP in determining criterion weights (range 0.09-0.50) and SAW in producing the best alternative rankings. Despite having different approaches, these methods consistently demonstrate the ability to analyze multi-criteria comprehensively, offering an objective perspective in complex decision-making [22].

The process of selecting scholarship recipients is very important and requires a structured approach. Research by Arslantaş applied Multi-Criteria Decision Making (MCDM) methods, such as AHP, SAW, and TOPSIS, to select students who best meet the criteria for receiving scholarships based on eight criteria, including Grade Point Average (GPA) and family income. Their findings show that the GPA criterion has the highest weight, 0.230, emphasizing the importance of academic achievement in the selection process [23]. In addition, a study by Suartini reported that the AHP-SAW method achieved an accuracy of 88.14% in selecting private tutors, indicating the effectiveness of this method in data-driven decision making [24] . The MADM approach can be applied in predicting student careers, where more objective decisions can support students in realizing their potential [25]. By applying a systematic method, student career decision-making can be optimized, providing benefits for students and educational institutions.

3 Research Method

This research focuses on the comparison between the Analytical Hierarchy Process (AHP) and Simple Additive Weighting (SAW) methods in predicting student career interests at SMAN 1 Karanganyar Demak, involving around 1113 students as the research population. Random sampling ensures balanced representation across class levels by considering class proportions. Data collection was conducted through a questionnaire specifically designed to explore student career interests, integrating various important criteria such as academic achievement, learning motivation, and social support received from the surrounding environment. This research uses a systematic approach to analyze student professional persistence, focusing on Decision Support Systems (DSS) and student career endurance. systematic architecture for exploring student professional adaptability potential through a comprehensive DSS approach. The research workflow initiates with an in-depth literature study, focusing on constructing a conceptual framework related to sustainability dynamics in secondary education contexts.

The data collection stage through student surveys represents a critical component of the research methodology. This process involves utilizing multidimensional data collection instruments designed to capture the complexity of factors influencing career trajectories. Two advanced analytical methods, Analytic Hierarchy Process (AHP) and Simple Additive Weighting (SAW), are integrated to dissect and analyze the collected data through complementary approaches. The AHP method enables researchers to perform structural hierarchy in criteria assessment, while SAW provides a precise weighting and normalization mechanism. The combination of these approaches creates a robust analytical framework, allowing extraction of profound insights into student career potential. The ultimate research outcome is a comprehensive prediction that can serve as a foundation for strategic interventions in career guidance. The stages of the research flow are shown in Figure 1.

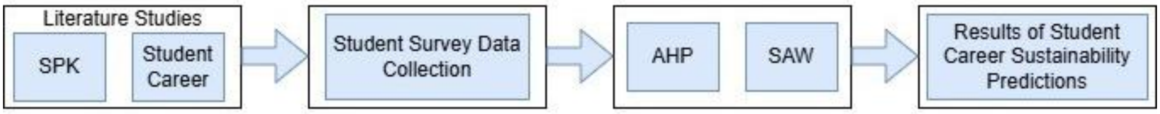

Figure 1. Research method

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By adopting a quantitative approach, data collected through questionnaires are then analyzed using two Multi-Attribute Decision Making (MADM) methods, namely Analytical Hierarchy Process (AHP) and Simple Additive Weighting (SAW). The AHP method serves to determine the relative weight of each criterion, while SAW is used to calculate the final score of each alternative based on the predetermined weights. This process not only produces accurate and appropriate recommendations, but also provides deeper insights into the factors that influence students' career decisions.

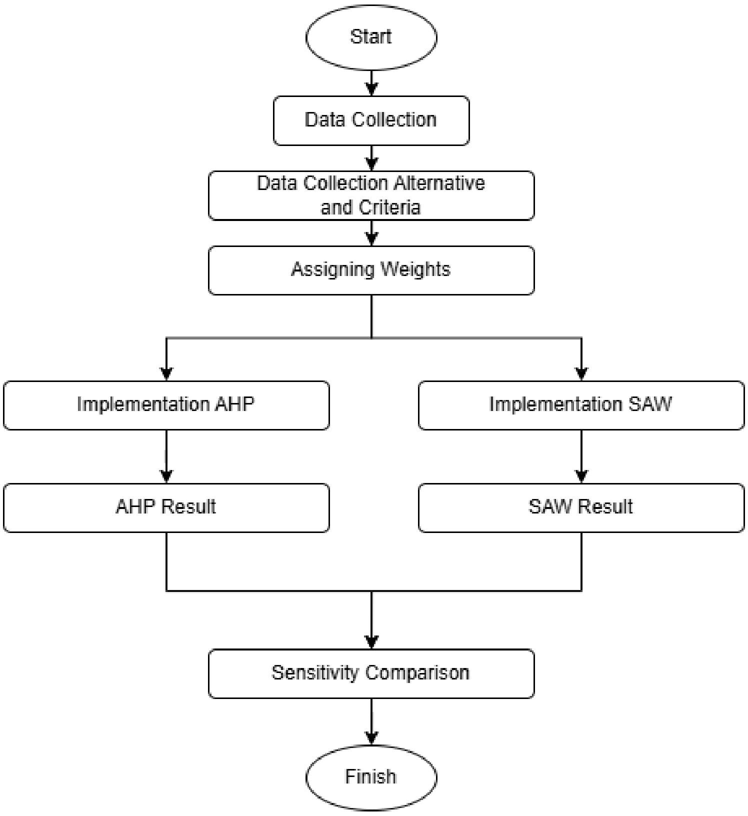

Figure 2. Research workflow diagram

Figure 2 represents this research methodology adopts a systematic methodology for implementing the Analytic Hierarchy Process (AHP) and Simple Additive Weighting (SAW) methods in a multicriteria decision analysis context. Each stage is meticulously designed to ensure the validity and reliability of the research process.

The flow begins with data collection, a critical foundation in decision model construction. In this phase, researchers conduct a comprehensive identification of relevant alternatives and criteria, using a systematic approach to extract substantive information from diverse data sources. The data collection process is not merely about gathering numbers, but creating a quantitative representation of the complexity of the studied phenomenon.

The subsequent stage involves weight assignment, where each criterion is deeply evaluated to determine its relative significance. AHP and SAW implementations are conducted in parallel, enabling sophisticated comparative analysis. These two methods produce specific outputs - AHP with its structural hierarchy and SAW with its additive weighting mechanism.

The pinnacle of the research process is sensitivity comparison, where results from both methods are critically examined to identify consistency, variations, and methodological implications. This final stage allows researchers to draw comprehensive conclusions and provide evidence-based recommendations. The unique approach integrates quantitative assessments with qualitative considerations, creating a more objective selection mechanism. The research concludes with opportunities for future performance evaluation models [26].

3.1. Data Collection

This research uses Python tools such as Pandas and NumPy to manipulate and explore the education dataset. The first dataset is an Excel dataset that has been analyzed and validated. The

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second stage of data collection involved the development of a score classification, which transformed numerical data into meaningful information. This method not only categorizes the data but also distributes the data, providing a comprehensive understanding of the research sample. The use of interactive modules such as IPython.display and matplotlib.pyplot enhances modern data analysis, enabling visualization and information representation.

Table 1. Descriptive analysis of dataset

Column	Mean	Median	Std Dev	Min	Max	Low	Very Low	Very High	Medium
Gender	0,58	1,00	0,49	0,00	1,00	58,13%	41,87%		
Goals	0,60	1,00	0,59	0,00	2,00	49,15%	45,46%	5,39%	
Father's Education	3,17	3,00	0,95	1,00	5,00	29,38%	29,20%	5,93%	35,49%
Learning Effectiveness	3,23	3,00	0,80	1,00	5,00		65,59%	4,58%	29,83%
Learning Preference	2,81	3,00	1,10	1,00	5,00	26,15%	48,25%	9,97%	15,63%

This research began in August 2024 using a Likert scale survey, through comprehensive descriptive statistical analysis. Table 1 Descriptive Analysis of Dataset, the gender variable shows a fairly balanced gender composition, but with 58.13% in the low category and 41.87% in the very low category. Students' aspirations have a mean of 0.60 and high variability, with 49.15% low, 45.46% very low, and only 5.39% very high. Father's education as an indicator of socio-cultural capital has a mean of 3.17, with 29.38% low, 29.20% very low, 5.93% very high, and 35.49% medium. Learning Effectiveness has a mean of 3.23, with 65.59% very low, 4.58% very high, and 29.83% medium. Learning Preference has a mean of 2.81 and the highest standard deviation of 1.10, with 26.15% low, 48.25% very low, 9.97% very high, and 15.63% medium.

3.2. Data Processing

Comprehensive Dataset covers 7 main criteria, providing deep insights into the heterogeneity of educational experiences (August 2024). Quantitatively, the score distribution shows significant variation in each criterion. The Family criterion shows an average score range of 2.5-3.5, indicating diverse socio-economic backgrounds. The Learning criterion records an average score of 3-4.5, revealing variations in the quality of educational interactions. With a score range of 2.5–4, student ability highlights the variety of personal skills. Academic Performance ranges from 3-4.5, reflecting achievements influenced by complex factors. School Resources with scores of 3-4.5 depict institutional infrastructure and support. The criteria for sustainability in careers, with a range of 3-4, explores students' future projections. Academic Interest, with scores of 2.5-4.5, reveals intrinsic motivations that cannot be simply predicted.

Table 2. Indicator criteria

Criteria	Criteria Code	Type
Family	C1	Cost
Learning	C2	Benefit
Student Potential	C3	Benefit
Academic Value	C4	Benefit
School Resources	C5	Benefit
Career Sustainability	C6	Benefit
Academic Interest	C7	Benefit

Table 2 Indicator Criteria, presents a comprehensive framework for understanding the complexity of educational dynamics. It identifies family as a cost variable, with C1 defining the educational trajectory. C2 to C7 are benefit criteria, indicating positive potential in measuring student

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quality and capacity. C2 emphasizes the educational transformation process and individual capabilities, while C4 and C5 reflect infrastructure and systemic achievements. C6 and C7 explore future dimensions and sustainable orientation of student profiles. Statistical analysis reveals no uniform score distribution, highlighting the systemic nature of education. The AHP approach allows for weighting considering complexity, transcending the conventional quantitative approach, offering a deep navigational map for understanding education's multidimensional dynamic.

3.3. AHP Analysis

Analytic Hierarchy Process (AHP) Multi-Attribute Decision Making (MADM) in this research is to produce a more objective and systematic decision-making system [27]. Priority comparisons are displayed in matrix form, and the scales filling the matrix are used using the Likert scale, and explanations for this scale are available in Table 3 Comparison Criteria.

Table 3. Comparison criteria

Criteria	Criteria Code	Intensity of Importance (1-5)	Definition
Family	C1	2,6	Sufficiently Important
Learning	C2	3,59	Important
Student Potential	C3	3,43	Sufficiently Important
Academic Value	C4	3,33	Sufficiently Important
School Resources	C5	3,38	Sufficiently Important
Career Sustainability	C6	3,62	Important
Academic Interest	C7	3,05	Sufficiently Important

Table 3. Comparison Criteria, presents the comparison of AHP criteria showing various aspects assessed in decision making. Family Criteria (C1) has a value of 2.6, indicating a fairly important significance. Learning (C2) with a value of 3.59 and Career (C6) which received 3.62 are considered important. Meanwhile, the criteria of emerging talent (C3), Academic Value (C4), and School Resources (C5) have values of 3.43, 3.33, and 3.38 respectively, indicating significant relevance. The next step is the AHP calculation process, among others:

AHP Normalization

$$\frac{Criteria\ Column\ Value}{Z\ Column} \tag{1}$$

The Analytic Hierarchy Process (AHP) initiates its analytical journey through a meticulous column normalization technique that transcends traditional data transformation approaches. Equation (1) is used to AHP normalization. This initial stage involves a sophisticated aggregation of raw numerical values, where each column's entries undergo a strategic normalization process. By dividing individual values against the column's total sum, the methodology converts raw numerical data into representative priority weights, enabling a more nuanced and precise comparative analysis. Sum the values of each column, then normalize by dividing the value of each column by the total value of all columns. Perform calculations to obtain the Priority Weight value [28].

Eigen vector

$$\lambda = \frac{Z\ Row}{Column} \tag{2}$$

The subsequent eigen vector computation delves deeper into the data's intrinsic structure, unveiling hidden patterns and relational dynamics, in Equation (2). This mathematical approach transforms pairwise comparison matrices into an advanced numerical representation, extracting strategic insights that illuminate the relative contributions of each criterion within the decision-making framework. The technique goes beyond simple numerical manipulation, offering a sophisticated lens for understanding complex hierarchical relationships [29].

Seeking Maximum Lambda Value

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$$\lambda\, Maks = \frac{(\lambda 1\; x \sum \quad Row\ 1) + \_ + (\lambda nx \sum \quad Row\ n)}{n} \tag{3}$$

$\lambda\, Maks = 7{,}2671\ (maximum\ lambda\ value)$
n =7 (number of criteria)

Determining the maximum lambda value emerges as a critical validation point, serving as a methodological cornerstone for assessing data consistency. Equation (3) shows the process of calculating the maximum lambda value. Through a systematic calculation involving the aggregation of weights across rows and columns, researchers can identify fundamental indicators of comparison matrix quality. [30]. In this specific analysis, the maximum lambda value of 7.2671 was observed across seven distinct criteria, providing a robust mathematical foundation for further evaluation.

Determine the CI and CR values

$$C1 = \frac{\lambda max - n}{n-1} = \frac{\mathbf{7{,}2671-7}}{7-1} = \frac{0{,}2671}{6} = 0{,}0445 \tag{4}$$

The consistency index (CI) calculation represents a nuanced approach to quantifying potential deviations from ideal consistency. Equation (4) illustrates the calculation of the Consistency Index. Utilizing the mathematical formula, the method precisely measures the divergence between the maximum lambda value and the total number of criteria [31]. The resulting value of 0.0445 indicates a minimal deviation, suggesting a high degree of internal logical coherence within the constructed hierarchical structure.

$$CR = \frac{CI}{IR} = \frac{0{,}0445}{1{,}32} = 0{,}0337 \tag{5}$$

The peak of this analysis lies in the consistency ratio (CR) calculation, which combines the consistency index with the random index (RI) to provide a comprehensive perspective on data reliability [32]. With a CR value of 0.0337 (3.37%), this analysis indicates a very good level of consistency, The obtained Consistency Ratio (CR) is 0.0337. The pairwise comparison matrix is consistent and suitable for AHP analysis since the CR value is less than 0.1, shown in Equation (5).

3.4. SAW Analysis

Decision making using the SAW methodology begins with the identification of key parameters that form the basis of the assessment. Next, an assessment is made of each available option by classifying its value according to predetermined criteria, followed by the assignment of weights that represent the significance of each criterion in the evaluation process.

This indicates that SAW needs a way to normalise the chosen matrix (X) to a scale that is accessible for its computations and can be compared across all alternatives [33]. The following are the stages involved in the SAW technique calculation: 1. Choose the names of the criteria that will be applied while making decisions. 2. Ascertain how each criterion of the chosen options is ranked within those alternatives. 3. Give an evaluation of the established weighting of each criterion name. 4. The normalisation matrix R with the equation is the outcome of the normalisation of the matrix or framework based on the conditions provided by the kind of criterion, whether benefit or cost, as seen in Equation (6).

Normalisation matrix R equation

$$r_{ij} \begin{cases} \dfrac{X_{ij}}{MaxX_{ij}} & if\ j\ is\ an\ attribute\ of\ profit\ (benefit) \\ \dfrac{MinxX_{ij}}{X_{ij}} & if\ j\ is\ a\ cost\ attribute\ (cost) \end{cases} \tag{6}$$

Where:
r_{ij} = Normalized performance rating
$MaxX_{ij}$ = Maximum value from each row and column
$MaxX_{ij}$ = Minimum value from each row and column

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X_{ij} = Row and column matrix

The final result calculation is obtained from the summation, especially the summation of the total value from the multiplication of the normalization matrix r. In Equation (7), the calculation method is presented. The highest value chosen as the best alternative is taken from this summation [34]. With the assumption :

$$Vi = \sum_{j=1}^{n} w_j r_{ij} \tag{7}$$

4 Results and Discussion

This research explores the complex dynamics in predicting students' career interests using two analytical approaches: Analytic Hierarchy Process (AHP) and Simple Additive Weighting (SAW). The focus of this research is to reveal the fundamental factors that influence career decisions in the secondary education environment, particularly at SMAN 1 Karanganyar Demak. By utilizing multi-criteria decision-making techniques, to understand the complexity of factors influencing students' professional choices. This research is not merely about data collection, but rather creating an analytical framework that enables in-depth understanding of individual potential.

4.1. AHP

To generate weighting values for each criterion, calculations need to be performed using the AHP method based on the indicator criteria, presented in the Table 4. Pairwise Comparison Matrix.

Table 4. Pairwise comparison matrix

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	1	2,702248	1,825607	4,888493	3,066691	3,956945	1,954937
C2	0,370062	1	1,121468	1,631133	1,421164	3,667371	4,270255
C3	0,547763	0,891688	1	4,22962	1,166276	3,635792	1,692789
C4	0,204562	0,613071	0,236428	1	3,204913	2,837511	3,831591
C5	0,326084	0,703649	0,85743	0,312021	1	4,285993	4,56234
C6	0,25272	0,272675	0,275043	0,352422	0,233318	1	1,646226
C7	0,511526	0,234178	0,590741	0,260988	0,219186	0,60745	1

The characteristics of the matrix show an interesting internal consistency, with each diagonal element valued at 1 and maintaining the reciprocal property that is a fundamental principle in AHP analysis. This indicates that each criterion has equal weight and consideration when compared to itself, while allowing for complex variations in inter-criteria comparisons.

Table 5. Results of pairwise comparison normalization

Criteria	C1	C2	C3	C4	C5	C6	C7
C1	0,311263	0,421074	0,309073	0,38569	0,297404	0,197936	0,103119
C2	0,115187	0,155824	0,189863	0,128692	0,137823	0,183451	0,225247
C3	0,170498	0,138946	0,169299	0,333706	0,113104	0,181871	0,089291
C4	0,063673	0,095531	0,040027	0,078897	0,310808	0,141939	0,202108
C5	0,101498	0,109645	0,145162	0,024618	0,096979	0,214395	0,240653
C6	0,078662	0,042489	0,046564	0,027805	0,022627	0,050022	0,086835
C7	0,159219	0,03649	0,100012	0,020591	0,021256	0,030386	0,052748

Presented in the Table 5. Results of Pairwise Comparison Normalization analysis of the constellation of criteria in decision-making shows the deep complexity of interconnection networks among various factors. Findings indicate that C1 has the highest connectivity with C2 (0.421074) and C4 (0.38569), forming a fundamental decision architecture. Criterion C2 displays the strongest relationship with C7 (0.225247), while C3 shows a significant correlation with C4 (0.333706). The interaction between C4 and C5 reaches the highest intensity (0.310808), with additional strong connections between C5 and C7 (0.240653) and C6 (0.214395), indicating a complex non-linear

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decision network. In the hierarchy of priority weights, C1 stands out spectacularly with a weight of 0.289365, dominating nearly 29% of the overall decision structure. Criteria C2 and C3 display interesting characteristics with relatively balanced priority weights (0.162298 and 0.170959), forming a secondary backbone in the decision-making process. They create a second layer in the hierarchy of importance, playing a crucial role in maintaining decision complexity.

Table 6. Relative priority results

Criteria	Total of Each Row	Total Priority
C1	2,025560	0,2893657
C2	1,136090	0,1622986
C3	1,196720	0,1709600
C4	0,932983	0,1332833
C5	0,932950	0,1332786
C6	0,355005	0,0507150
C7	0,420703	0,0601004

Table 6. Relative Priority Results shows C4 and C5 show their own uniqueness with very similar priority weights, 0.133283 and 0.133279 respectively - a mathematical coincidence that indicates a close relationship between the criteria. Although they have a more limited influence compared to the main criteria, both still make a significant contribution in building a comprehensive decision narrative. Criteria C6 and C7 act as peripheral elements in the structure, with priority weights of 0.0507151 and 0.0601004. Although they have minimal influence, C6 and C7.

Table 7. Matrix of addition for each row

Criteria	C1	C2	C3	C4	C5	C6	C7	Total
C1	0,311263	0,421074	0,309073	0,38569	0,297404	0,197936	0,103119	2,025558
C2	0,115187	0,155824	0,189863	0,128692	0,137823	0,183451	0,225247	1,136085
C3	0,170498	0,138946	0,169299	0,333706	0,113104	0,181871	0,089291	1,196715
C4	0,063673	0,095531	0,040027	0,078897	0,310808	0,141939	0,202108	0,932983
C5	0,101498	0,109645	0,145162	0,024618	0,096979	0,214395	0,240653	0,93295
C6	0,078662	0,042489	0,046564	0,027805	0,022627	0,050022	0,086835	0,355005
C7	0,159219	0,03649	0,100012	0,020591	0,021256	0,030386	0,052748	0,420703

Table 7. Matrix of Addition for Each Row explains the prominent criteria C1 with a total of 2.02556, displaying its central role in the overall analysis structure. The highest value in C1 is seen in C2 (0.421074) and C4 (0.38569), indicating a strong correlation and significant influence on these criteria. Criteria C2 and C3 show an interesting interaction pattern, with total sums of 1.13609 and 1.19672 respectively. C2 exhibits uniqueness in its relationship with C7, where the highest value reaches 0.225247, while C3 has the strongest connection with C4 at 0.333706. This reveals that although not as dominant as C1, these two criteria play an important role in decision-making.

C4 and C5 present an impressive mathematical narrative, with almost similar interaction characteristics but a unique nuance. C4, with a total sum of 0.932983, displays the most intense relationship with C5 at 0.310808, creating a distinct node of interest within the matrix. C5 also shows a similar pattern, with the strongest connections to C7 (0.240653) and C6 (0.214395). Criteria C6 and C7, although having the lowest total sums (0.355005 and 0.420703 respectively), should not be overlooked. They are like supporting actors who provide depth and complexity to the entire system.

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C6 exhibits the most significant interaction with C5 (0.214395), while C7 has the strongest relationship with C2 (0.225247), underscoring their subtle yet important roles.

Table 8. Consistency ratio calculation

Criteria	Total of Each Row	Total Priority	Result
C1	2,025560	0,2893657	0,586127616
C2	1,136090	0,1622986	0,184385784
C3	1,196720	0,1709600	0,204591251
C4	0,932983	0,1332833	0,12435104
C5	0,932950	0,1332786	0,124342243
C6	0,355005	0,0507150	0,018004079
C7	0,420703	0,0601004	0,025284431
Total			1,267086444

```
Consistency Ratio Analysis:
Lambda Max     : 7.2671
Consistency Index (CI) : 0.0445
Consistency Ratio (CR)  : 0.0337
Random Index (RI)      : 1.3200

Criteria Priority Table:
Criteria  Row Total  Priority Sum  Priority Percentage  Priority Decimal  Total
      C1     2.0256        0.2894              28.9366            0.2894 0.5861
      C2     1.1361        0.1623              16.2299            0.1623 0.1844
      C3     1.1967        0.1710              17.0960            0.1710 0.2046
      C4     0.9330        0.1333              13.3283            0.1333 0.1244
      C5     0.9329        0.1333              13.3279            0.1333 0.1243
      C6     0.3550        0.0507               5.0715            0.0507 0.0180
      C7     0.4207        0.0601               6.0100            0.0601 0.0253
```

Figure 3. Consistency ratio calculation result

Table 8. Consistency Ratio Calculation shows the results of the calculation Calculation of Consistency Ratio between criteria. Further AHP analysis shows an acceptable level of consistency in decision making. The Maximum Lambda value of 7.2671 indicates the stability of the comparison matrix assessment. Consistency Index (CI) 0.0445 and Consistency Ratio (CR) 0.0337 or 3.37% are well below the 10% threshold, indicating a very consistent and reliable assessment. The priority analysis of the criteria reveals that Criterion 1 Family (C1) has the highest priority weight of 28.94%, followed by C3 occupational potential 17.10% and C2 Learning 16.23%. C4 Academic Value and C5 School Resources have a balanced weight of around 13.33%, while C7 Academic Interest 6.01% and C6 Professional sustainability 5.07% have relatively small influence, as shown in the calculation results in Figure 3. Consistency Ratio Calculation Result.

4.2. SAW

The SAW method integrates several criteria that reflect the complexity of the educational context. C1 Family reveals the socio-economic landscape of parents that affects individual potential. C2 Learning delves into cognitive mechanisms and learning preferences. C3 Student performance focuses on mapping intrinsic capabilities. C4 Academic Value integrates cross-disciplinary assessments. C5 School Resources evaluates the readiness of educators and the quality of the institutional ecosystem. C6 explores motivational aspects through the projection of students' interests and beliefs. And C7 Academic Interest, which can represent students' interest in the academic field, is interpreted in the alternative values of each SAW criterion in Table 9. Alternative Values for Each SAW Criterion.

Table 9. Alternative values for each saw criterion

No	Name	C1	C2	C3	C4	C5	C6	C7
1	Arina Dwi Puspitasari	1,50	3,67	4,00	3,50	3,50	4,00	3,50
2	A. Bagas Wahyu S.	2,50	4,00	2,00	3,25	3,00	3,50	5,00
3	Abdul Hakim	2,00	4,00	3,00	3,00	3,00	3,00	4,50

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4	Abdul Kholid Huda Ashofa	2,50	3,33	3,33	3,25	3,00	4,00	2,50
5	Abdul Rozak	2,17	3,67	2,00	1,75	1,50	3,00	3,00
6	Abdullah Masum	3,00	3,00	3,00	3,00	3,00	3,00	3,00
7	Achmad Ibra Dinova	3,50	3,67	3,67	3,75	4,50	4,00	4,00
8	Achmad Noor Saifuddin	2,17	2,67	2,67	2,75	2,00	3,50	2,50
…	…	…	…	…	…	…	…	…
1113	Zunita Tri Widiyanti	2,33	3,67	4,00	3,00	4,50	3,50	3,50

Table 10. Criteria weight values

Criteria	Type	Average	Weight
Family(C1)	Cost	2,598682	0,112909732
Learning(C2)	Benefit	3,593591	0,15613736
Student Potential(C3)	Benefit	3,433363	0,149175656
Academic Performance(C4)	Benefit	3,325696	0,144497651
School Resources(C5)	Benefit	3,384996	0,147074132
Career Sustainability(C6)	Benefit	3,624438	0,157477651
Academic Interest(C7)	Benefit	3,054807	0,132727817
Total			1

Table 10. Criteria Weight Values, further analysis reveals that the C6 has the highest weight of 15.75% with an average of 3.624, emphasizing the importance of future projections in the context of education. C2 occupies the second position with a weight of 15.61% and an average of 3.594, emphasizing the learning process as the core of intellectual capacity building. C3 with a weight of 14.92% and an average of 3.433 encourages a more personalized education model. C5 with a weight of 14.71% and an average of 3.385 emphasizes the importance of supporting infrastructure and ecosystem. Further in Table 11. Normalized Matrix Calculation Results shows that the relatively balanced distribution of weights between the benefit criteria reflects the need for a contextual, adaptive, and non-linear evaluation model.

Table 11. Normalized matrix calculation results

No	ALTERNATIVE	C1	C2	C3	C4	C5	C6	C7
1	Arina Dwi Puspitasari	0,333333	0,733333	0,8	0,7	0,285714	0,8	0,7
2	A. Bagas Wahyu S.	0,555556	0,8	0,4	0,65	0,333333	0,7	1
3	Abdul Hakim	0,444444	0,8	0,6	0,6	0,333333	0,6	0,9
4	Abdul Kholid Huda Ashofa	0,555556	0,666667	0,666667	0,65	0,333333	0,8	0,5
5	Abdul Rozak	0,481481	0,733333	0,4	0,35	0,666667	0,6	0,6
…	…	…	…	…	…	…	…	…
1108	Ziska Abelia	0,592593	0,933333	0,6	0,9	0,222222	0,8	0,5
1109	Zulia Rahman	0,592593	0,933333	0,866667	0,6	0,333333	0,6	1
1110	Zuliani Akhir Al Meka	0,333333	0,733333	0,466667	0,6	0,25	0,8	0,5
1111	Zumrotun Kaisya	0,62963	0,666667	0,666667	0,7	0,25	0,8	0,4
1113	Zunita Tri Widiyanti	0,518519	0,733333	0,8	0,6	0,222222	0,7	0,7

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The results of the normalization matrix calculation in Table 11. Normalized Matrix Calculation Results show the distribution of the values of the alternatives analyzed, then continued by summing the matrices in Table 12. Matrix Addition Result.

Table 12. Matrix addition result

No	Name	C1	C2	C3	C4	C5	C6	C7	Total
1	Arina Dwi Puspitasari	0,087054	0,11	0,12	0,174	0,028571	0,08	0,07	0,669625
2	A. Bagas Wahyu S.	0,140625	0,12	0,06	0,162	0,033333	0,07	0,1	0,685958
3	Abdul Hakim	0,116071	0,12	0,09	0,15	0,033333	0,06	0,09	0,659405
4	Abdul Kholid Huda Ashofa	0,147321	0,1	0,1	0,162	0,033333	0,08	0,05	0,672655
5	Abdul Rozak	0,131696	0,11	0,06	0,09	0,066667	0,06	0,06	0,578363
…	…	…	…	…	…	…	…	…	…
1109	Ziska Abelia	0,151786	0,14	0,09	0,222	0,022222	0,08	0,05	0,756008
1110	Zulia Rahman	0,147321	0,14	0,13	0,15	0,033333	0,06	0,1	0,760655
1111	Zuliani Akhir Al Meka	0,084821	0,11	0,07	0,15	0,025	0,08	0,05	0,569821
1112	Zumrotun Kaisya	0,162946	0,1	0,1	0,174	0,025	0,08	0,04	0,681946
1113	Zunita Tri Widiyanti	0,138393	0,11	0,12	0,15	0,022222	0,07	0,07	0,680615

After the matrix is normalized, the next step is the preference value process for each alternative. Determination of the ranking process using the weights obtained from the decision making and then carrying out the process by first multiplying the r value by the weight of the criteria to get the alternative value with the largest value, displayed in Table 13. Comparison of AHP and SAW.

Table 13. Comparison of AHP and SAW

Recommendation Category	AHP (%)	SAW (%)	Difference (%)
Needs Guidance	42,68	46,00	+3,32
Working	33,96	32,97	-0,99
College	12,94	10,06	-2,88
Entrepreneur	10,42	10,96	+0,54

The comparative analysis between Analytic Hierarchy Process (AHP) and Simple Additive Weighting (SAW) reveals critical methodological distinctions beyond mere numerical variations. Critically, while both methods demonstrate an overall accuracy of 83.02%, their underlying computational philosophies generate substantively different interpretations of learning potential. The Need for Guidance category (AHP: 42.68%; SAW: 46.00%) highlights a fundamental divergence: AHP's approach suggests structural barriers requiring intervention, whereas SAW indicates more immediate, pragmatic support requirements. This nuanced difference implies that AHP provides a more hierarchical, contextual understanding of student challenges, while SAW offers a more direct, linear assessment of intervention needs.

The Working category (AHP: 33.96%; SAW: 32.97%) reveals remarkable methodological consistency, suggesting robust alignment in evaluating career readiness. However, the College and Entrepreneurial categories expose deeper methodological variations. AHP's higher College recommendation percentage (12.94% vs. SAW's 10.06%) suggests a more academically-oriented

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assessment framework that potentially overemphasizes traditional educational pathways. Performance metrics further illuminate these methodological nuances. The Need for Guidance category's high F1-score (0.91) demonstrates sophisticated intervention identification, while the College category's precision (0.97) indicates strong predictive capabilities for academic trajectories. Conversely, the Entrepreneur category's lower F1-score (0.60) reveals potential limitations in capturing complex entrepreneurial potential across both methodological approaches. In the end, the study questions traditional models of decision-making by showing that AHP and SAW are sophisticated interpretative frameworks that provide multifaceted insights into student prospective, rather than merely computational tools. Each approach offers a distinct viewpoint on long-term professional development and personal potential. A table comparing career suggestions for the top 10 rated students using the Analytical Hierarchy Process (AHP) and Simple Additive Weighting (SAW) approaches is presented in Table 14. Top Rows Based on Total Score.

Table 14. 10 Top rows based on total score

No	Name	SAW Score	SAW Career Recommendation	AHP Score	AHP Career Recommendation
568	Marfatus Solekah	0,937440	College	0,161875	College
1111	Tasya Anaya Putri	0,888571	College	0,161250	College
1049	Wardatul Farihah	0,859812	College	0,160625	College
436	Irfan Nur Rahmatullah	0,875258	College	0,159375	College
246	Diah Bunga Ayu Ning Tyas	0,867490	College	0,158750	College
504	Linanda Ayu K.N	0,900946	College	0,158750	College
939	Shafira Nabila	0,846571	College	0,157500	College
237	Dewi Amelia Ramadhani	0,876173	College	0,156875	College
62	Alya Azzahra	0,878690	College	0,156875	College
686	Muhammad Zidane Arai Putra	0,872911	College	0,156875	College

5 Conclusion

This study provides information on how MADM techniques more especially, AHP and SAW can be used to forecast career interests. According to the analysis's findings, the Family (C1) criterion has the highest priority weight (28.94%), indicating that parents' socioeconomic status has a big impact on their children's academic ability. With weights of 16.23% and 17.10%, respectively, the Learning (C2) and Student Capabilities (C3) criteria highlight the significance of both the learning process and personal skills in identifying career pathways. The research results show that both methods, AHP and SAW, are able to provide accurate career recommendations with an accuracy rate of 83.02%. The Needs Guidance category emerges as the main recommendation with a proportion of 42.68% for AHP and 46.00% for SAW, indicating the need for ongoing support for students in planning their future. Work Category shows a slight decrease of 0.99 points, from 33.96% (AHP) to 32.97% (SAW), indicating relative consistency in assessing students' ability to enter the workforce. Meanwhile, the College recommendation experienced a more significant decline of 2.88 points, dropping from 12.94% to 10.06%, which may reflect differences in assessment weights between the two methods. Entrepreneurship Category displays minimal variation with an increase of 0.54 points, from 10.42% to 10.96%. This small difference suggests consistency in assessing students' entrepreneurial potential across the two analysis methods. The study compares AHP and SAW, showing similar distribution patterns of recommendations, but differences in certain categories. Both methods are effective in decision-making, contributing to the development of personalized career guidance strategies. This research serves as a reference for better career prediction models and encourages MADM methods in broader educational contexts.

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