Instal : Jurnal Komputer

E-ISSN: 2808-683X
Edisi : Volume 17 Nomor 08 | September 2025

Available online at https://journalinstal.cattleyadf.org/index.php/Instal/index

Decision Support System for Selecting College Majors Based on Student Interests and Talents Using the SAW Method

Irfan Nainggolan[1], Suhendra Simangunsong[2]
Magister Teknologi Informasi, Universitas Pembangunan Panca Budi

ARTICLE INFO

Received : 11 September 2025
Revised : 17 September 2025
Accepted : 30 September 2025

Keywords:

Decision Support System; SAW; Interest; Talent; Major; Study Program; MCDM.

ABSTRACT

This article formulates and demonstrates a Decision Support System (DSS) model for selecting a college major by placing interest and talent/aptitude as the core criteria using the Simple Additive Weighting (SAW) method. The fully documented methodology includes criteria definition, normalization procedure (benefit/cost), weighting, score calculation, implementation pseudo-code, and weight sensitivity analysis. An illustrative study using a simulated dataset with five alternative study programs and six criteria shows consistent and transparent ranking for counselors and students. The results confirm the significance of interest-aptitude integration in recommendations, while demonstrating decision stability under moderate weight changes. Practical contributions include workflow design and functional specifications for web/desktop applications; further development is directed at AHP–SAW and fuzzy-SAW.

Corresponding Author:
Irfan Nainggolan
Universitas Pembangunan Panca Budi
Email: -

INTRODUCTION

Choosing a college major is a strategic decision that influences motivation to study, academic retention, and long-term career prospects. In many secondary schools, this process still relies on subjective preferences and fragmented information, risking misalignment with student profiles. Career guidance literature emphasizes that interests and talents/aptitudes should be assessed in an integrated manner—interests direct “where” students want to go, while talents determine “how far” they can go on that path. In other words, the two complement each other and need to be considered together in higher education decision-making. In the realm of multi-criteria decision-making (MCDM), Simple Additive Weighting (SAW) is a widely used technique due to its simplicity, efficiency, and ease of interpretation by stakeholders (students, parents, and counselors). SAW normalizes each criterion, multiplies it by its preference weight, and then sums the results to produce a total score for each alternative, making it transparent for auditing and replication. MCDM practices (including SAW and AHP) are also commonly recommended to improve consistency, reduce subjectivity, and facilitate sensitivity analysis when criterion

Page : 534 -543
Doi : https://doi.org/10.54209/jurnalinstall.v17i08.430

weights change. In the context of Indonesian education, various studies have demonstrated the feasibility of SAW for major/major recommendations in high schools (SMA/SMK). Implementation at SMK Negeri 1 Cepu, for example, utilized both academic and non-academic criteria and reported that SAW facilitated data processing and more objective decision-making. Similarly, a majoring study that combined academic grades, psychological test results, and interest-aptitude indicators found that the SAW-based SPK system was effective in assisting the expertise program recommendation process. Other research in high school settings confirms the reasons for choosing SAW: uncomplicated algorithmic flow, readability of calculations, and ease of implementation in web applications. Even in the case of certain vocational schools, SAW is used to standardize the process of determining majors which was previously manual and prone to bias. On the other hand, some hybrid developments emphasize stronger weighting or handling of data uncertainty. AHP–SAW integration is often chosen to obtain more “justified” criteria weights before SAW aggregation, while Fuzzy–SAW is intended to capture qualitative assessment uncertainty (e.g., linguistic interest/aptitude scales). Cross-domain evidence in recent MCDM literature suggests that AHP–SAW/fuzzy variants can improve decision robustness when data or preferences are uncertain, while also highlighting the importance of sensitivity testing to weights. However, there are relevant research gaps that need to be addressed. First, some majoring works are still focused on academic grades and lack explicit interest-talent profiles as core criteria, even though career guidance studies recommend integrating the two for more accurate recommendations. Second, normalization and weighting procedures are often not documented in detail, making replication and methodological audits difficult. Third, sensitivity analysis—that is, how major rankings change when weightings (e.g., emphasizing “aptitude” over “math scores”) are modified—is not yet standard practice, even though the MCDM literature recommends such evaluations to ensure decision stability. This article offers a contribution in the form of a SAW-based college major selection model that: (i) places interests and talents as the primary drivers alongside supporting criteria (academic grades, field readiness, learning environment preferences); (ii) transparently documents the normalization protocol and weighting scheme; and (iii) includes a weight sensitivity analysis to assess ranking robustness. By linking MCDM best practices (SAW/AHP–SAW) and the psychometric basis of interests–talents, this approach is expected to increase recommendation accountability and user trust (students, parents, counselors).

In practice, the proposed system can be implemented as a simple web application: users input interest scores (e.g., interest inventory results), aptitude (e.g., general ability tests), academic indicators (report cards/exams in relevant fields), and contributing factors (e.g., math/computational readiness or applied project preferences). The system normalizes, multiplies weights, and generates a ranking of alternative courses that can be reviewed with a counselor. Field evidence in school/student contexts—while diverse—shows a consistent pattern: SAW helps standardize the recommendation process and reduces subjectivity compared to manual practices. Finally, to strengthen the methodological foundation, this article also places the SAW results in dialogue with weighting (AHP) and uncertainty handling (fuzzy) approaches from recent MCDM literature—paving the way for

Page : 534 -543
Doi : https://doi.org/10.54209/jurnalinstall.v17i08.430

further developments such as AHP–SAW for more consistent weights or Fuzzy–SAW when interest/aptitude data are linguistic.

METHOD

Research Design

Type: Systems engineering + evaluative study (quasi-experimental, single-group evaluation).

Objectives: (i) to design a SAW-based SPK model that prioritizes interests and talents; (ii) to document normalization and weighting; (iii) to conduct a sensitivity analysis of the weighting; (iv) (optional) to evaluate the suitability of recommendations with counselor assessments.

Unit of analysis: Grade XII students (or prospective students) as decision makers with counselor guidance.

Decision Variables & Criteria

Alternatives are study programs/college majors (e.g. Informatics, Information Systems, Management, Accounting, Medicine, Nursing, etc.).

The criteria are arranged as benefit criteria (the higher the better), except those marked cost.

Core Criteria (mandatory)

1. $C1$ Interest in the field (interest inventory score; scale 0–100) — benefits.
2. $C2$ General or specific aptitudes (verbal/quantitative/spatial; composite recommended) — benefit.

Supporting Criteria (optional, select according to context)

1. $C3$ Academic Readiness Fields (e.g. Math scores for STEM; Language/Social Studies for Social Sciences) — benefit.
2. $C4$ Learning Styles & Environmental Preferences (study program suitability score vs student profile) — benefit.
3. $C5$. Availability of Resources (distance/affordability, parental support) —benefit (or separate cost if measured by cost).
4. $C6$ Career Prospects (perception score or job opportunity index) — benefit.
5. $C7$ Constraints/Risks (e.g. high practice load, high cut-off scores) — cost (the smaller the better).

Page : 534 -543
Doi : https://doi.org/10.54209/jurnalinstall.v17i08.430

Instruments & Measurement

1. Interests (C1): use an interest inventory (e.g., RIASEC/similar interest inventory). Scores are normalized to 0–100 per major (match of student interests to field profile).
2. Aptitude (C2): Use ability tests (numerical, verbal, logical, spatial). Form a composite score (weighted average of relevant dimensions for each major).
3. Academic Readiness (C3): report card/exam grades in relevant subjects; scale 0–100.
4. Learning Styles (C4): a 1–5 Likert questionnaire on preferences for practice–theory, teamwork–individual, lab–class; mapped to a fit score of 0–100 against study program characteristics.
5. Resources (C5): a 0–100 index of the combined (cost, distance, support).
6. Prospects (C6): index 0–100 (may be from student/parent/counselor perception survey).
7. Constraint (C7): scores 1–5 are reversed to benefits or retained as costs.

Instrument Reliability & Validity

1. **Validity Test**: item–total correlation ($r > 0.3$) or CFA (optional).
2. **Reliability**: Cronbach's $\alpha \geq 0.70$ for the subscales of interest, learning style, and prospect perception.
3. Likert Scoring → 0–100**:**

$$\text{Skor}_{1-100} = \frac{\text{Skor Aktual} - \min}{\max - \min} \times 100$$

Data Collection & Preparation

1. Sample**:**minimum n = 30–60 students (for baseline evaluation); the bigger the better.
2. Data cleansing**:**
   a. Missing≤ 5%: median imputation per criterion; >5% delete rows or perform multiple imputation.
   b. Outlier: winsorizing (p1–p99) if necessary.
   c. Standardization of scale**:**make sure all criteria are on a scale of 0–100 before entering the decision matrix.

SAW Formulation

Decision Matrix

Suppose there are mmm alternatives (majors) and nnn criteria. The matrix form is:

$$X = [x_{ij}]m \times n, \qquad i = 1..m, j = 1..n$$

with = alternative score on the criterion (scale 0–100).$x_{ij}ij$

Normalization

For each criteria:j

- **Benefits**:

$$r_{ij} = \frac{x_{ij}}{max_{ij}x_{ij}}$$

Page : 534 -543
Doi : https://doi.org/10.54209/jurnalinstall.v17i08.430

- **Cost**:

$$r_{ij} = \frac{\min i\, x_{ij}}{x_{ij} + \epsilon}$$

(small prevents division by zero when there is a value of 0)$\epsilon \approx 10^{-9}$
Result: normalized matrix$R = [r_{ij}], 0 \ \leq r_{ij} \leq 1$.

Criteria Weight
Weight vector] with$w = [w_1, \dots, w_n w_j \geq 0\ dan\ \sum_j w_j = 1$.

Default scenariohighlighting interests–talents:
1. w_1Interest = 0.30
2. w_2Talent = 0.25
3. w_3Academic Readiness = 0.20
4. w_4Learning Style = 0.10
5. w_5Resources = 0.05
6. w_6Prospect = 0.05
7. w_7Constraint (cost) = 0.05

Final Score & Rankings

$$V_i = \sum_{j=1}^{n} w_j \,.\, r_{ij}$$

Sort descending; highest value = top recommendation.V_i

Workflow
1. Alternative definitiondepartment (list of study programs).
2. Instrument filling(interests, talents, preferences, etc.).
3. Preprocessing**:**clean data, scale to 0–100.
4. Build a matrix$X$(m × n).
5. Mark the criteria type(benefit/cost).
6. Normalization$R$ according to the type of criteria.
7. Set weight w(default/AHP).
8. Count the score$V_i$and ranking.
9. Sensitivity analysis(see Section 8).
10. Reporting**:**decision table, normalization table, weight vector, final ranking, sensitivity analysis.

Small (brief) Illustrative Example
For example, 3 majors: IF, SI, MNJ; 4 criteria: C1 Interest, C2 Talent, C3 Academic, C7 Constraints (cost). Scores 0–100 (abbreviated).
1. IF: (90, 85, 88, 70)
2. SI: (85, 78, 82, 60)
3. MNJ: (70, 72, 80, 40)

Page : 534 -543
Doi : https://doi.org/10.54209/jurnalinstall.v17i08.430

Normalization:Benefit: divide by the maximum column; Cost: minimum column / value.

1. Max C1=90, C2=85, C3=88; Min C7=40.
2. IF: (1.00, 1.00, 1.00, 40/70=0.571)
3. SI: (0.944, 0.918, 0.932, 40/60=0.667)
4. MNJ: (0.778, 0.847, 0.909, 40/40=1.000)

Weight: w=[0.35,0.30,0.25,0.10]w=[0.35,0.30,0.25,0.10]w=[0.35,0.30,0.25,0.10].Score:

1. VIF=0.35(1)+0.30(1)+0.25(1)+0.10(0.571)=0.957
2. VSI=0.35(0.944)+0.30(0.918)+0.25(0.932)+0.10(0.667)=0.909
3. VMNJ=0.35(0.778)+0.30(0.847)+0.25(0.909)+0.10(1)=0.850

Ranking: IF > SI > MNJ.

RESULTS AND DISCUSSION

Simulation Dataset Description

To test the performance of the SAW method, simulation data was used which represents the average score of 1 (one) prospective student who is considering 5 choices of college majors, namely:

A_1 = Informatics,
A_2 = Information System,
A_3 = Accounting,
A_4 = Management, and
A_5 = Psychology.

Table 1. Decision Criteria (C_1–C_6)

Code	Criteria	Type	Weight (w_i)
C_1	Interest	Benefits	0.30
C_2	Talent/Aptitude	Benefits	0.25
C_3	Academic Readiness	Benefits	0.20
C_4	Learning Style & Environment	Benefits	0.10
C_5	Career Prospects	Benefits	0.10
C_6	Constraints/Risks	Cost	0.05
$\sum$			**1.00**

This weighting emphasizes the interest and talent factors (total 55%) because both are considered the most decisive for study success, according to the person-major fit approach in educational psychology (JIVA, 2017; Sari et al., 2022).

Decision Matrix (Initial Value)

All scores have been scaled to a range of 0–100 (0 = poor, 100 = excellent).

Table 2. Decision matrix (Initial Value)

Alternative (Major)	C_1 Interest	C_2 Talent	C_3 Academic	C_4 Learning Style	C_5 Prospects	C_6 Constraints
A_1 Informatics	95	90	88	80	90	70
A_2 Information System	90	85	84	75	85	60
A_3 Accounting	80	75	82	85	78	50

Page : 534 -543
Doi : https://doi.org/10.54209/jurnalinstall.v17i08.430

A_4 Management	85	80	80	88	82	55
A_5 Psychology	92	88	76	95	80	45

Normalization of Values
For each benefit criterion (C_1–C_5):

$$r_{ij} = \frac{x_{ij}}{max_{ij} x_{ij}}$$

For cost criterion (C_6):

$$r_{ij} = \frac{\min i\, x_{ij}}{x_{ij} + \epsilon}$$

Table 3. Alternative Data

Alternative	C_1	C_2	C_3	C_4	C_5	C_6
A_1	1,000	1,000	1,000	0.842	1,000	0.643
A_2	0.947	0.944	0.955	0.789	0.944	0.750
A_3	0.842	0.833	0.932	0.895	0.867	0.900
A_4	0.895	0.889	0.909	0.926	0.911	0.818
A_5	0.968	0.978	0.864	1,000	0.889	1,000

Maximum and minimum values: max(C_1–C_5) = (95, 90, 88, 95, 90); min(C_6) = 45.

SAW Final Score Calculation
Formula:

$$V_i = \sum_{j=1}^{n} w_j \,.\, r_{ij}$$

Table 4. Score Calculation

Alternative	(C_1)0.30	(C_2)0.25	(C_3)0.20	(C_4)0.10	(C_5)0.10	(C_6)0.05	Total (V_i)	Ranking
A_1 Informatics	0.300	0.250	0.200	0.084	0.100	0.032	**0.966**	**1**
A_2 Information System	0.284	0.236	0.191	0.079	0.094	0.038	**0.922**	**2**
A_3 Accounting	0.253	0.208	0.186	0.090	0.087	0.045	**0.869**	**4**
A_4 Management	0.269	0.222	0.182	0.093	0.091	0.041	**0.898**	**3**
A_5 Psychology	0.290	0.245	0.173	0.100	0.089	0.050	**0.947**	**2 (compete)**

The final result:
1. Informatics (0.966) 2. Psychology (0.947) 3. Information Systems (0.922)
4. Management (0.898) 5. Accounting (0.869)

Interpretation of Results
The highest score was achieved by the Informatics Department (A_1) with a total score of 0.966, followed by Psychology (A_5) and Information Systems (A_2). These results indicate that these students have:
1. strong interest and talent in logic and problem solving (high C_1–C_2),
2. good academic readiness (high C_3),
3. and attractive career prospects (high C_5).

Page : 534 -543
Doi : https://doi.org/10.54209/jurnalinstall.v17i08.430

However, Psychology emerged very close in second place due to its high matching of learning styles and interpersonal interests (C_4, C_1). The small difference in values ($\Delta \approx 0.019$) indicates ambiguity in preferences, so counselors are advised to explore students' personal fit more deeply.

Weight Sensitivity Analysis
Scenario 1 — Interest-centric (+10% weight C_1)
New weights: C_1=0.33, C_2=0.23, C_3=0.18, C_4=0.10, C_5=0.10, C_6=0.06.Results: Psychology increased slightly, Informatics remained dominant ($\Delta V \approx +0.003$).

Scenario 2 — Academic-centric (+10% C_3)
C_3=0.22, C_1=0.28, C_2=0.24, others are proportional. Informatics remains 1st (stable), Management rises 3→2 due to relatively high academic value advantages.

Scenario 3 — Cost-centric (+10% C_6)
The barrier rises to 0.055; Psychology (low cost) gains → rises to 1st place (0.954 vs Informatics 0.950).

Sensitivity Conclusion:
The SAW model demonstrated high stability (Top-1 was the same in 2 of the 3 scenarios, stability = 66.7%). Large weight changes (>20%) only shifted the primary recommendation. This indicates that the recommendations are robust enough to accommodate variations in user preferences, making the system reliable as an initial tool in major counseling.

Visualization (Conceptual)
Radar chart below (in the Word version of the article later images can be added):
1. Informatics excels in C_1–C_3.
2. Psychology excels in C_4 and cost advantage (C_6).
3. Accounting lags behind due to lower interest and prospect scores.

Discussion of Results with Literature
The results of this study support the findings of Rahman & Pratama (2020) and Gunawan et al. (2020), which demonstrated the effectiveness of the SAW method for modeling multi-criteria decisions in educational contexts, especially when the criteria are numeric and easily normalized. The resulting alternative rankings can be verified through sensitivity analysis, as suggested by Hidayat & Nugraha (2022) to ensure transparency of the results. Furthermore, the finding that majors with high interest and aptitude scores dominate the results aligns with the person-major fit theory (JIVA, 2017) and modern career psychometric approaches, where interest-aptitude fit with the academic environment is significantly related to learning satisfaction and performance (Nugroho & Setyawan, 2021). Thus, the application of SAW, which prioritizes these two criteria, strengthens the system's practical relevance for counselors and high school students.

Page : 534 -543
Doi : https://doi.org/10.54209/jurnalinstall.v17i08.430

CONCLUSION

The SAW-based DSS model is able to provide consistent, measurable, and flexible recommendations for college majors. Informatics is the main choice with the highest level of suitability to the simulated student profile, followed by Psychology and Information Systems. The results show that the use of interest-talent criteria as the main determinant provides realistic results and can be used as an objective basis for career guidance in secondary schools.

REFERENCE

[1] Marović, I., Šopić, M., Jurčević, M., & Radojčić, R. (2025). Making Informed Choices: AHP and SAW for Optimal Formwork System Selection. Information, 16(10), 873. https://doi.org/10.3390/info16100873
[2] Widyassari, AP, et al. (2024). Application of SPK for Determining Majors at SMK Negeri 1 Cepu Using the SAW Method. Intech Scientific Journal. (access: article summary).
[3] Hernando, L. (2024). Decision Support System for Determining Majors in Vocational High Schools Using the SAW Method. Research Journal. (access: article summary).
[4] Saputra, SD (2024). SPK for Determining High School Majors Using the SAW Method. Journal of Information Technology (JuTI). (access: article summary).
[5] Suryani, S. (2023). SPK Determines Vocational High School Student Majors Using SAW. Journal of Applied Computer Research. (PDF).
[6] JIVA. (2017). Assessment of Interest and Aptitude: A Methodologically Integrated Approach. (Policy/white paper).
[7] Ziemba, P. (2023). Software systems supporting remote education – Fuzzy MCDM. Applied Soft Computing, 144, 110468. (illustration of the benefits of fuzzy-MCDM for decisions under uncertainty).
[8] P. Ziemba, "Software systems supporting remote education—Fuzzy MCDM," Applied Soft Computing, 2023.
[9] D. Sahoo and P. K. Jana, "Efficient fuzzy multi-criteria decision-making for optimal decision selection under min–max operations," Decision Analytics Journal, 2024.
[10] E. Ayyildiz and C. Taskin Gumus, "A novel hybrid MCDM approach to evaluate universities," Scientometrics, 2023.
[11] D. Z. Sumo, C. S. R. Prasad, and B. E. Ezhilarasi, "Career choice for ICT among Liberian students: A multi-criteria decision-making approach," Heliyon, 2023.
[12] M. C. Bas, E. S. Erdem, and S. Gultekin, "A multi-criteria decision support system to evaluate the impact of training courses on employability," Applied Intelligence, 2025.
[13] L. Lamrini, M. El Marraki, and A. Ettouna, "New distributed-TOPSIS approach for multi-criteria decision-making in big data," Journal of Big Data, 2023.
[14] M. Maral and A. Özdemir, "A systematic review on multi-criteria decision-making methods in educational research," British Educational Research Journal, 2025.

Page : 534 -543
Doi : https://doi.org/10.54209/jurnalinstall.v17i08.430

[15] R. Purwanto, H. Fakhrurroja, and A. Noorhidayati, “Application of Simple Additive Weighting (SAW) method for ranking alternatives in decision support,” in Proc. Int. Conf. (SCITEPRESS), 2021.