



Paper Type: Original Article

Career Selection Using Single-Valued Neutrosophic Sets and Normalized Euclidean Distance Method

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Citation:

Received: 17 October 2024
Revised: 22 January 2025
Accepted: 10 March 2025

Das, P. (2025). Career selection using single-valued Neutrosophic sets and normalized euclidean distance method. *Transactions on soft computing*, 1(3), 183-189.

Abstract

Career selection involves incomplete, indeterminate, and sometimes conflicting information. This article represents both student profiles and career requirements by single-valued neutrosophic triples and compares them with a normalized Euclidean distance. The normalization is corrected to use all three coordinates, ensuring that every reported distance lies in $[0, 1]$. A four-student, four-career illustration is recomputed from the supplied profile tables. The resulting nearest-profile recommendations are anatomy for student s_1 , surgery for s_2 , and pharmacy for both s_3 and s_4 . In particular, the recalculation corrects the earlier assignment of medicine to s_3 . A decision-margin certificate is also introduced: if the difference between the two smallest distances exceeds twice the maximum distance-estimation error, the recommendation cannot change under that perturbation. The example is intended as a transparent decision-support demonstration, not as a validated psychological or educational assessment. Real use requires expert elicitation of the career profiles, appropriate subject weights, and validation against independent student outcomes.

Keywords: Single-valued Neutrosophic set, Career selection, Normalized Euclidean Distance, Decision support, Uncertainty, Sensitivity margin.

1 | Introduction

Career selection is a multi-attribute decision problem. Academic performance is relevant, but a realistic decision may also depend on interests, aptitude, personality, access to

training, financial constraints, and personal preferences. These inputs are rarely known without uncertainty. A mathematical model should therefore distinguish a strong match, incomplete evidence, and evidence against a match instead of compressing all information into one score.

Fuzzy sets assign one membership grade to each object [1]. Intuitionistic fuzzy sets add an explicit non-membership grade subject to a consistency restriction [2]. Single-valued neutrosophic sets use independent truth, indeterminacy, and falsity components in $[0, 1]$, making them suitable for data that contain unresolved or inconsistent assessments [4]. Distance-based comparison then provides a transparent way to rank a student profile against a collection of career profiles.

The source manuscript proposed such a comparison but contained several mathematical and numerical problems. The coordinates were not used consistently, the displayed Euclidean normalization did not guarantee a value in $[0, 1]$, one table entry had a punctuation error, and the reported distance table could not be reproduced from the supplied profiles. The present version resolves these issues, recomputes every distance, and adds a stability margin for interpreting close decisions.

The method is deliberately modest. It is a nearest-profile decision-support rule, not a causal model of career success. Its output is meaningful only when the profile values and subject weights have been elicited and validated for the population in which the method is used.

2 | Mathematical Preliminaries

2.1 | Fuzzy and Intuitionistic Fuzzy Descriptions

Let $X = \{x_1, \dots, x_n\}$ be a finite universe. A fuzzy set A is represented by a membership function $\mu_A : X \rightarrow [0, 1]$ [1]. An intuitionistic fuzzy set assigns both membership $\mu_A(x)$ and non-membership $\nu_A(x)$, satisfying

$$0 \leq \mu_A(x) + \nu_A(x) \leq 1.$$

The residual quantity $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ is interpreted as hesitation or incomplete information [2, 5].

2.2 | Single-Valued Neutrosophic Sets

Definition 2.1. A single-valued neutrosophic set (SVNS) A on X is

$$A = \{\langle x, T_A(x), I_A(x), F_A(x) \rangle : x \in X\},$$

where $T_A, I_A, F_A : X \rightarrow [0, 1]$ are the truth-membership, indeterminacy-membership, and falsity-membership functions, respectively. For every $x \in X$,

$$0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3.$$

The three SVNS coordinates are independent; their sum is not required to equal one. A fuzzy description can be embedded by taking $I_A(x) = 0$ and $F_A(x) = 1 - T_A(x)$. An intuitionistic fuzzy description is obtained when $T_A(x) + F_A(x) \leq 1$ and $I_A(x) = 1 - T_A(x) - F_A(x)$. The single-valued formulation avoids the nonstandard interval notation used in general neutrosophic-set definitions and is the appropriate form for the numerical application considered here [4].

2.3 | Normalized Euclidean Distance

Let A and B be two SVNSe on the same n -element universe. For each x_j , write

$$q_j(A, B) = (T_A(x_j) - T_B(x_j))^2 + (I_A(x_j) - I_B(x_j))^2 + (F_A(x_j) - F_B(x_j))^2.$$

Define

$$d_N(A, B) = \left[\frac{1}{3n} \sum_{j=1}^n q_j(A, B) \right]^{1/2}. \quad (1)$$

This is the ordinary Euclidean distance between the $3n$ -dimensional profile vectors, scaled by $1/\sqrt{3n}$. It extends the principle that every available membership coordinate should enter a distance calculation [5, 6].

Proposition 2.2. *For all SVNSe profiles A, B, C , the function d_N satisfies*

$$0 \leq d_N(A, B) \leq 1, \quad d_N(A, B) = 0 \iff A = B,$$

is symmetric, and satisfies the triangle inequality.

Proof. Each of the $3n$ squared coordinate differences is at most one, so the expression inside the square root is at most one. The remaining properties follow from the corresponding properties of the Euclidean norm after multiplication by the positive constant $1/\sqrt{3n}$. $\square$

If subject weights $w_j \geq 0$ satisfy $\sum_{j=1}^n w_j = 1$, the weighted version is

$$d_w(A, B) = \left[\frac{1}{3} \sum_{j=1}^n w_j q_j(A, B) \right]^{1/2}. \quad (2)$$

Equation (1) is recovered when $w_j = 1/n$.

3 | Career-Selection Model

Let

$$\mathcal{S} = \{s_1, s_2, s_3, s_4\}$$

be the student set and

$$\mathcal{C} = \{\text{medicine, pharmacy, surgery, anatomy}\}$$

be the candidate-career set. The subject universe is

$$X = \{\text{English, mathematics, biology, physics, chemistry}\}.$$

For each subject, a profile contains a triple (T, I, F) . In a validated implementation, these components must be generated by a stated scoring or expert-elicitation protocol. In the present illustration, the values are retained from the supplied manuscript and treated as illustrative inputs.

For a student s and career c , compute $d_N(s, c)$ from Eq. (1). The nearest-profile recommendation is

$$c^*(s) \in \arg \min_{c \in \mathcal{C}} d_N(s, c). \quad (3)$$

If several careers attain the same minimum, all tied careers should be reported rather than broken by an unstated rule.

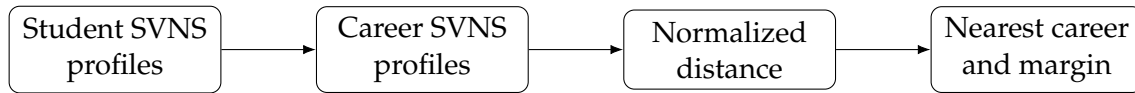


Figure 1. Transparent nearest-profile workflow for career decision support.

3.1 | Career Profiles

Table 1 lists the four career profiles. The malformed surgery–physics entry in the source, $(0.5, 0.4, 0.3)$, has been corrected to $(0.5, 0.4, 0.3)$.

Table 1. Illustrative career profiles; every entry is ordered as (T, I, F) .

Career	English	Mathematics	Biology	Physics	Chemistry
Medicine	$(.8, .1, .2)$	$(.7, .2, .3)$	$(.9, .0, .2)$	$(.6, .3, .2)$	$(.8, .1, .2)$
Pharmacy	$(.9, .1, .1)$	$(.8, .1, .4)$	$(.8, .1, .3)$	$(.5, .3, .3)$	$(.7, .2, .3)$
Surgery	$(.5, .3, .4)$	$(.5, .2, .3)$	$(.9, .0, .2)$	$(.5, .4, .3)$	$(.7, .1, .4)$
Anatomy	$(.7, .2, .3)$	$(.5, .4, .2)$	$(.9, .1, .3)$	$(.6, .3, .4)$	$(.8, .0, .3)$

3.2 | Student Profiles

The four student profiles are given in Table 2. These are not observations from a documented cohort and should not be interpreted as empirical data.

Table 2. Illustrative student profiles; every entry is ordered as (T, I, F) .

Student	English	Mathematics	Biology	Physics	Chemistry
s_1	$(.6, .3, .2)$	$(.5, .4, .2)$	$(.6, .2, .3)$	$(.5, .3, .3)$	$(.5, .5, .1)$
s_2	$(.5, .3, .4)$	$(.6, .2, .3)$	$(.5, .3, .4)$	$(.4, .5, .2)$	$(.7, .2, .3)$
s_3	$(.7, .1, .3)$	$(.6, .3, .2)$	$(.7, .1, .3)$	$(.5, .4, .3)$	$(.4, .5, .2)$
s_4	$(.6, .4, .1)$	$(.8, .1, .4)$	$(.6, .1, .4)$	$(.6, .3, .2)$	$(.5, .3, .4)$

4 | Recomputed Results

Applying Eq. (1) to Tables 1 and 2 gives Table 3. All values were recomputed directly from the displayed triples and rounded to four decimal places.

The recalculation confirms anatomy for s_1 , surgery for s_2 , and pharmacy for s_4 . It changes the source manuscript's recommendation for s_3 from medicine to pharmacy because

$$d_N(s_3, \text{pharmacy}) = 0.1653 < d_N(s_3, \text{medicine}) = 0.1751.$$

Table 3. Corrected normalized Euclidean distances and nearest-profile recommendations.

Student	Medicine	Pharmacy	Surgery	Anatomy	Recommendation
s_1	0.1983	0.1966	0.1897	0.1880	Anatomy
s_2	0.1966	0.1915	0.1528	0.1826	Surgery
s_3	0.1751	0.1653	0.1770	0.1862	Pharmacy
s_4	0.1789	0.1438	0.1770	0.2066	Pharmacy

4.1 | Decision-Margin Certificate

Let $d_{(1)}(s)$ and $d_{(2)}(s)$ be the smallest and second-smallest distances for student s , and define the decision margin

$$\Delta(s) = d_{(2)}(s) - d_{(1)}(s).$$

Proposition 4.1. *Suppose every reported student-career distance changes by at most η . If $\Delta(s) > 2\eta$, the nearest-profile recommendation for student s cannot change under those perturbations.*

Proof. The smallest distance can increase by at most η , while every competing distance can decrease by at most η . Therefore, the original gap remains positive whenever $\Delta(s) - 2\eta > 0$. $\square$

Table 4. Decision margins for the illustrative recommendations.

Student	Best career	Runner-up	Margin Δ
s_1	Anatomy	Surgery	0.0017
s_2	Surgery	Anatomy	0.0298
s_3	Pharmacy	Medicine	0.0098
s_4	Pharmacy	Surgery	0.0332

The recommendation for s_1 is especially fragile because its margin is only 0.0017. Such a result should be presented as a near tie. The larger margins for s_2 and s_4 indicate greater separation within this particular illustrative profile system, but they do not establish external validity.

5 | Interpretation and Limitations

The model offers three practical advantages. First, every comparison is transparent: a recommendation can be traced to subject-level truth, indeterminacy, and falsity coordinates. Second, the normalized distance has a fixed range, enabling comparisons across applications with the same construction. Third, the margin distinguishes a clear nearest profile from an unstable near tie.

Several limitations are essential. The tables are illustrative and were not obtained from a documented survey, examination protocol, or longitudinal cohort. The same weights were assigned to all five subjects, although real career requirements may place different importance on them. The neutrosophic coordinates require an explicit elicitation and calibration procedure; otherwise, they are subjective labels. The model also omits interests,

personality, financial and geographic constraints, disability accommodations, labour-market information, and student preferences.

Consequently, the procedure must not be used as an automated gatekeeper. It is better interpreted as one component of a counselling process in which students inspect the profile comparisons, discuss uncertainty with qualified advisers, and retain final control over their choices. Before empirical claims are made, the method should be evaluated prospectively using independent outcomes and compared with simpler baselines.

6 | Conclusion

A corrected single-valued neutrosophic framework for career selection has been presented. The method represents student and career profiles by independent truth, indeterminacy, and falsity grades and compares them with a properly normalized Euclidean distance. Recalculation of the supplied example produces anatomy for s_1 , surgery for s_2 , and pharmacy for s_3 and s_4 . The revised calculation corrects the former recommendation for s_3 and exposes the near tie for s_1 . A simple perturbation-margin certificate indicates when a nearest-profile decision is stable to bounded distance errors. The example demonstrates mathematical transparency, while its use as an actual career-guidance tool requires calibrated profiles, validated weights, broader student information, and independent empirical evaluation.

Author Contributions

All authors contributed equally.

Funding

The funding statement must be confirmed by the author before publication.

Data Availability

No external dataset was used. All illustrative career and student profiles are reproduced in Tables 1 and 2.

Competing Interests

The competing-interests statement must be confirmed by the author before publication.

Generative-AI assistance

Generative AI assisted with language, LaTeX preparation and technical representation of the paper.

References

- [1] Zadeh, L. A. (1965). Fuzzy sets. *Information and control*, 8(3), 338–353. [https://doi.org/10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X)
- [2] Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy sets and systems*, 20(1), 87–96. [https://doi.org/10.1016/S0165-0114\(86\)80034-3](https://doi.org/10.1016/S0165-0114(86)80034-3)
- [3] Smarandache, F. (1999). *A unifying field in logics: Neutrosophy, Neutrosophic probability, set and logic*. American Research Press.
- [4] Wang, H., Smarandache, F., Zhang, Y.-Q., & Sunderraman, R. (2010). Single valued neutrosophic sets. *Multispace and Multistructure*, 4, 410–413.
- [5] Szmidt, E., & Kacprzyk, J. (2000). Distances between intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, 114(3), 505–518. [https://doi.org/10.1016/S0165-0114\(98\)00244-9](https://doi.org/10.1016/S0165-0114(98)00244-9)
- [6] Szmidt, E. (2014). *Distances and Similarities in Intuitionistic Fuzzy Sets*. Springer. <https://doi.org/10.1007/978-3-319-01640-5>
- [7] Türksen, I. B. (1986). Interval valued fuzzy sets based on normal forms. *Fuzzy Sets and Systems*, 20(2), 191–210. [https://doi.org/10.1016/0165-0114\(86\)90077-1](https://doi.org/10.1016/0165-0114(86)90077-1)