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# Type-2 Neutrosophic Sets (T2NSs) for Quality Evaluation of Project-Based Art and Design Courses: Evaluation Seven Projects

# Ruijuan Zhang\*

Zhengzhou University of Industrial Technology, Zhengzhou, 451150, Henan, China \*Corresponding author, E-mail: zike963852@163.com

Abstract: Conflicting objectives for alternatives must be valued in a decision-making process, and the optimal option must be chosen based on the decision-makers requirements. For this selection, multi-objective optimization techniques might offer a solution. The purpose of this study is to introduce two relatively new multi-objective optimization techniques: multi-objective optimization based on simple ratio analysis (MOOSRA) and Entropy methods. This study uses the multi-criteria decision-making method (MCDM) to evaluate the project-based art and design courses. The entropy method is used to compute the criteria weights and the MOOSRA method is used to rank the alternatives. The MCDM method is used under the type-2 neutrosophic sets (T2NSs) to deal with vague and uncertain information. A case study with 14 criteria and seven projects are used in this study. The results show that Graphic Design Projects have the highest rank and the Product & Industrial Design has the lowest rank. Sensitivity analysis was conducted to show the different ranks of alternatives.

**Keywords**: Type-2 Neutrosophic Sets; Projects Arts and Design Courses; Uncertainty; Entropy; MOOSRA method.

#### 1. Introduction

Zadeh suggested fuzzy set theory as an extension of classical sets. Following Zadeh's work, scholars became interested in fuzzy set theory, and the number of academic papers on the topic has grown significantly across a range of fields, including the social sciences, engineering, and economics[1], [2]. A membership function is used to describe a fuzzy set. The idea of linguistic truth and fuzzy sets, whose membership levels are described using language terms like low, medium, high, very low, not low, not high, etc., are closely related. Conversely, one could think of a fuzzy set A as a mapping from discourse universe U to subsets of the interval [0, 1] that is defined by a membership function containing linguistic factors.

As a generalization of fuzzy sets, Atanassov presented the idea of intuitionistic fuzzy sets. Two functions known as membership and non-membership functions define an intuitionistic fuzzy

set. An essential tool for modeling situations involving reluctance is an intuitionistic fuzzy set[3], [4]. Studies on the theoretical elements of intuitionistic fuzzy sets and their applications in decision-making problems have been growing quickly since Atanassov established the idea.

Important tools for modeling uncertainty-related problems include the fuzzy set, intuitionistic fuzzy set, type-2 fuzzy set, and type-2 intuitionistic fuzzy set. These ideas help model uncertainty, but they might not be enough to explain some problems with contradictory data. The primary cause of this deficiency is the distinction between the ideas of uncertainty and inconsistency. The idea of inconsistency conveys meaninglessness among outcomes produced under the same conditions, but the idea of uncertainty conveys deficiencies or fuzziness of results[5], [6]. For instance, a decision-maker may respond to the same question in a "positive" or "negative" manner at various times.

This demonstrates how inconsistent the decision-maker is. The statement "it is positive between 0.6 and 0.8" or "0.7 positive" indicates that the person making the decision is unsure of the answer to the question, indicating that there is some hesitation. Therefore, Smarandache created the neutrosophic set theory to solve inconsistency-related difficulties. An extension of the intuitionistic, classical, fuzzy, paraconsistent, dialetheist, paradoxist, and tautological sets based on neutrosophy is known as a neutrosophic set[7], [8]. The field of philosophy known as "neutrosophy" examines the genesis, characteristics, and application of neutralities.

According to neutrosophy, a statement, theory, event, concept, or entity "A" is compared to its opposite "Anti-A," something that is not A, "Non-A," and anything that is neither "A" nor "Anti-A," represented by "Neut-A." From a universal set to a real or non-real standard subset, a neutrosophic set is defined by three functions[9], [10]. They are known as the truth-membership function, falsity-membership function, and indeterminacy membership function, and they are independent of one another. While the neutrosophic set theory is useful for modeling some problems, it is not always a good fit for modeling engineering challenges[11], [12].

Abdel Basset et al. [13] recently defined the concept of type-2 neutrosophic numbers (T2NNs) by defining arithmetical and set-theoretical operations between T2NNs and assigning truth-membership, indeterminacy membership, and falsity-membership values to components of a single-valued neutrosophic number[14], [15]. They also introduced several ideas, including T2NN aggregating operators and score and accuracy functions.

Among the multi-objective optimization techniques is the MOOSRA approach. When the MOOSRA and MOORA methods are compared, the MOOSRA technique is less sensitive to significant fluctuations in the criterion values and does not exhibit the negative performance scores of the MOORA approach. To rank the options, it was utilized to create the MCDM framework[16], [17].

The MOORA approach and the MOOSRA method have comparable application steps. Specifically, the problem's decision matrix is constructed in the first stage, and the decision matrix

is then normalized in the second. The MOOSRA technique uses a straightforward ratio of the total of the normalized performance values for advantageous criteria to the total of the normalized performance values for non-beneficial criteria to determine the overall performance score of each alternative[18], [19].

The main contributions of this study are organized as follows:

- This study uses two MCDM approaches to select the best project. The entropy method is used to compute the criteria weights and the MOOSRA method is used to rank the alternatives.
- This study evaluated the criteria and alternatives of projects based on art design. We use
   14 criteria and seven alternatives in this study.
- The T2NSs are used to deal with uncertainty and vague information in the evaluation process between the criteria and alternatives.

This is how the remainder of the paper is structured: First, the T2NSs and their operations are conducted. Secondly, the Entropy and MOOSRA approaches' respective methodological underpinnings are presented. Then, using seven projects to be evaluated under different criteria. Then we show the sensitivity analysis. Finally, the applications' outcomes are shown, and suggestions for further research are talked about.

## 2. Type-2 Neutrosophic Sets (T2NSs)

Let two type-2 neutrosophic numbers (T2NNs) such as[13]:

$$A_{1} = \left( \left( T_{T_{A_{1}}}(x), T_{I_{A_{1}}}(x), T_{F_{A_{1}}}(x) \right), \left( I_{T_{A_{1}}}(x), I_{I_{A_{1}}}(x), I_{F_{A_{1}}}(x) \right), \left( F_{T_{A_{1}}}(x), F_{I_{A_{1}}}(x), F_{F_{A_{1}}}(x) \right) \right) \text{ and }$$

$$A_{2} = \left( \left( T_{T_{A_{2}}}(x), T_{I_{A_{2}}}(x), T_{F_{A_{2}}}(x) \right), \left( I_{T_{A_{2}}}(x), I_{I_{A_{2}}}(x), I_{F_{A_{2}}}(x) \right), \left( F_{T_{A_{2}}}(x), F_{I_{A_{2}}}(x), F_{F_{A_{2}}}(x) \right) \right)$$

$$A_{1} \oplus A_{2} = \begin{pmatrix} T_{T_{A_{1}}}(x) + T_{T_{A_{2}}}(x) - T_{T_{A_{1}}}(x) T_{T_{A_{2}}}(x), \\ T_{I_{A_{1}}}(x) + T_{I_{A_{2}}}(x) - T_{I_{A_{1}}}(x) T_{I_{A_{2}}}(x), \\ T_{T_{A_{1}}}(x) + T_{T_{A_{2}}}(x) - T_{T_{A_{1}}}(x) T_{T_{A_{2}}}(x), \\ T_{T_{A_{1}}}(x) + T_{T_{A_{2}}}(x), I_{I_{A_{1}}}(x) T_{I_{A_{2}}}(x), I_{F_{A_{1}}}(x) T_{F_{A_{2}}}(x) \right), \\ \left( I_{T_{A_{1}}}(x) I_{T_{A_{2}}}(x), I_{I_{A_{1}}}(x) I_{I_{A_{2}}}(x), I_{F_{A_{1}}}(x) I_{F_{A_{2}}}(x) \right), \\ \left( F_{T_{A_{1}}}(x) F_{T_{A_{2}}}(x), F_{I_{A_{1}}}(x) F_{I_{A_{2}}}(x), F_{F_{A_{1}}}(x) F_{F_{A_{2}}}(x) \right) \right)$$

$$A_{1} \otimes A_{2} = \begin{pmatrix} \left(T_{T_{A_{1}}}(x)T_{T_{A_{2}}}(x), T_{I_{A_{1}}}(x)T_{I_{A_{2}}}(x), T_{F_{A_{1}}}(x)T_{F_{A_{2}}}(x)\right), \\ I_{T_{A_{1}}}(x) + I_{T_{A_{2}}}(x) - I_{T_{A_{1}}}(x)I_{T_{A_{2}}}(x), \\ I_{I_{A_{1}}}(x) + I_{I_{A_{2}}}(x) - I_{I_{A_{1}}}(x)I_{I_{A_{2}}}(x), \\ I_{F_{A_{1}}}(x) + I_{F_{A_{2}}}(x) - I_{F_{A_{1}}}(x)I_{F_{A_{2}}}(x) \end{pmatrix}, \\ \begin{pmatrix} F_{T_{A_{1}}}(x) + F_{T_{A_{2}}}(x) - F_{T_{A_{1}}}(x)F_{T_{A_{2}}}(x), \\ F_{I_{A_{1}}}(x) + F_{I_{A_{2}}}(x) - F_{I_{A_{1}}}(x)F_{I_{A_{2}}}(x), \\ F_{F_{A_{1}}}(x) + F_{F_{A_{2}}}(x) - F_{F_{A_{1}}}(x)F_{F_{A_{2}}}(x) \end{pmatrix}$$

$$A_{1}^{\lambda} = \begin{pmatrix} \left( \left( T_{T_{A_{1}}}(x) \right)^{\lambda}, \left( T_{T_{A_{1}}}(x) \right)^{\lambda}, \left( T_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( \left( 1 - \left( 1 - I_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - I_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - I_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\ \left( 1 - \left( 1 - F_{T_{A_{1}}}(x) \right)^{\lambda} \right), \\$$

## 3. Materials and Methods

This section shows the proposed approach under the T2NSs to compute the criteria weights and rank the alternatives. This study uses two MCDM methods such as the Entropy method to compute the criteria weights and the MOOSRA method to rank the alternatives. We used the T2NSs to deal with vague and uncertain data. Figure 1 shows the proposed approach to computing the criteria weights and ranking the alternatives.

Terms of T2NSs	T2NNs
Very Low	((0.20,0.20,0.10), (0.65,0.80,0.85), (0.45,0.80,0.70))
Low	((0.35,0.35,0.10), (0.50,0.75,0.80), (0.50,0.75,0.65))
Medium Low	((0.50,0.30,0.50), (0.50,0.35,0.45), (0.45,0.30,0.60))
Medium	((0.40,0.45,0.50), (0.40,0.45,0.50), (0.35,0.40,0.45))
Medum High	((0.60,0.45,0.50), (0.20,0.15,0.25), (0.10,0.25,0.15))
High	((0.70,0.75,0.80), (0.15,0.20,0.25), (0.10,0.15,0.20))
Very High	((0.95,0.90,0.95), (0.10,0.10,0.05), (0.05,0.05,0.05))

Table 1. The T2NNs.

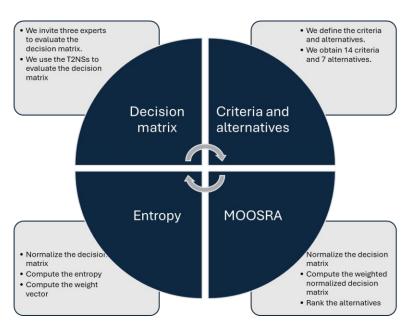


Figure 1. The process of MCDM methods.

# 3.1 T2NSs-Entropy Method

This part uses the Entropy method under the T2NSs to compute the criteria weights. The steps of the proposed approach are organized as follows:

### Step 1. Build the decision matrix.

We used the linguistic terms of the T2NSs to build the decision matrix by the experts. Then we replace these terms by using the T2NNs as shown in Table 1. Then we apply the score function to obtain the one value. Then we aggrege the decision matrix between the criteria and alternatives.

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}$$
 (5)

# Step 2. Normalize the decision matrix.

The decision matrix is normalized between the criteria and alternatives such as:

$$P_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}}; i = 1, \dots, m; j = 1, \dots, n$$
(6)

Step 3. Compute the entropy

The entropy number is computed such as:

$$n_{j} = -h \sum_{i=1}^{m} p_{ij} \ln p_{ij} \tag{7}$$

$$h = \frac{1}{\ln(m)} \tag{8}$$

Step 4. Compute the weight vector.

The weight vector between the criteria is computed such as:

$$w_j = \frac{1 - n_j}{\sum_{j=1}^n (1 - n_j)} \tag{9}$$

#### 3.2 T2NSs-MOOSRA Method

The MOOSRA method is the MCDM method used to rank the alternatives. It is a multi-objective optimization method. The steps of the MOOSRA method are organized as:

Step 5. Normalize the decision matrix.

We start with the combined decision matrix. Then we normalize the decision matrix between the criteria and the alternatives such as:

$$q_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{10}$$

Step 6. Compute the weighted normalized decision matrix.

The weighted normalized decision matrix between the criteria and the alternatives is computed as:

$$d_{ij} = w_j q_{ij} \tag{11}$$

Step 7. Rank the alternatives.

The alternatives are ranked based on the highest score in each row in the weighted normalized decision matrix.

$$f_i = \frac{\sum benefit\ value}{\sum non\ benefit\ value} \tag{12}$$

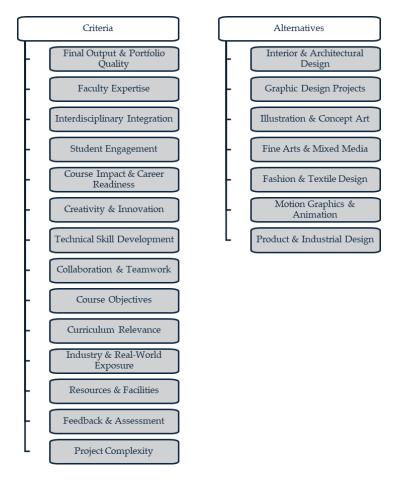


Figure 2. The criteria and types of projects.

### 4. Results and Analysis

This section shows the results of the evaluation of art and design project courses. This study collects 14 criteria and seven projects to be evaluated. Three experts have evaluated the criteria and alternatives. Figure 2 shows the criteria and alternatives.

## 4.1 Results T2NSs-Entropy Method

Three experts initially evaluated the criteria and alternatives using the terms listed in Table 1. These qualitative terms were then converted into their corresponding T2NN values, as detailed in Table 2, and subsequently combined into a single comprehensive matrix. In Step 2, Equation (6) is applied to normalize this decision matrix, with the normalized values presented in Table 3. Following this, Step 3 involves using Equation (7) to compute the entropy, which helps in understanding the degree of variation in the data. Finally, in Step 4, Equation (9) is used to calculate the weight vector, as illustrated in Figure 3.

	A1	A2	<b>A</b> 3	$A_4$	A5	A <sub>6</sub>	A <sub>7</sub>
$C_1$	((0.20,0.20,0.10),	((0.20,0.20,0.10),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.70,0.75,0.80),	((0.60,0.45,0.50),	((0.40,0.45,0.50),
	(0.65, 0.80, 0.85),	(0.65,0.80,0.85),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.15,0.20,0.25),	(0.20, 0.15, 0.25),	(0.40, 0.45, 0.50),
	(0.45,0.80,0.70))	(0.45, 0.80, 0.70))	(0.05,0.05,0.05))	(0.05, 0.05, 0.05))	(0.10,0.15,0.20))	(0.10,0.25,0.15))	(0.35, 0.40, 0.45))

Table 2. The T2NNs between criteria and alternatives.

$C_2$	((0.35, 0.35, 0.10),	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.35,0.35,0.10),	((0.50,0.30,0.50),
	(0.50,0.75,0.80),	(0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.50,0.75,0.80),	(0.50,0.35,0.45),
	(0.50, 0.75, 0.65))	(0.10,0.15,0.20))	(0.05, 0.05, 0.05))	(0.05, 0.05, 0.05))	(0.45, 0.80, 0.70))	(0.50,0.75,0.65))	(0.45, 0.30, 0.60))
Сз	((0.50,0.30,0.50),	((0.70,0.75,0.80),	((0.20,0.20,0.10),	((0.40,0.45,0.50),	((0.60,0.45,0.50),	((0.50,0.30,0.50),	((0.35,0.35,0.10),
	(0.50, 0.35, 0.45),	(0.15,0.20,0.25),	(0.65, 0.80, 0.85),	(0.40,0.45,0.50),	(0.20,0.15,0.25),	(0.50,0.35,0.45),	(0.50,0.75,0.80),
	(0.45,0.30,0.60))	(0.10,0.15,0.20))	(0.45,0.80,0.70))	(0.35,0.40,0.45))	(0.10,0.25,0.15))	(0.45,0.30,0.60))	(0.50,0.75,0.65))
$C_4$	((0.40, 0.45, 0.50),	((0.60,0.45,0.50),	((0.35,0.35,0.10),	((0.50,0.30,0.50),	((0.70,0.75,0.80),	((0.40,0.45,0.50),	((0.20,0.20,0.10),
	(0.40,0.45,0.50),	(0.20,0.15,0.25),	(0.50,0.75,0.80),	(0.50,0.35,0.45),	(0.15,0.20,0.25),	(0.40,0.45,0.50),	(0.65,0.80,0.85),
	(0.35,0.40,0.45))	(0.10,0.25,0.15))	(0.50,0.75,0.65))	(0.45,0.30,0.60))	(0.10,0.15,0.20))	(0.35,0.40,0.45))	(0.45,0.80,0.70))
$C_5$	((0.60,0.45,0.50),	((0.40,0.45,0.50),	((0.50,0.30,0.50),	((0.35,0.35,0.10),	((0.95,0.90,0.95),	((0.60,0.45,0.50),	((0.70,0.75,0.80),
	(0.20,0.15,0.25),	(0.40,0.45,0.50),	(0.50,0.35,0.45),	(0.50,0.75,0.80),	(0.10,0.10,0.05),	(0.20,0.15,0.25),	(0.15,0.20,0.25),
	(0.10,0.25,0.15))	(0.35,0.40,0.45))	(0.45,0.30,0.60))	(0.50,0.75,0.65))	(0.05,0.05,0.05))	(0.10,0.25,0.15))	(0.10,0.15,0.20))
C <sub>6</sub>	((0.70,0.75,0.80),	((0.50,0.30,0.50),	((0.40,0.45,0.50),	((0.20,0.20,0.10),	((0.95,0.90,0.95),	((0.70,0.75,0.80),	((0.60,0.45,0.50),
	(0.15,0.20,0.25),	(0.50,0.35,0.45),	(0.40,0.45,0.50),	(0.65,0.80,0.85),	(0.10,0.10,0.05),	(0.15,0.20,0.25),	(0.20,0.15,0.25),
_	(0.10,0.15,0.20))	(0.45,0.30,0.60))	(0.35,0.40,0.45))	(0.45,0.80,0.70))	(0.05,0.05,0.05))	(0.10,0.15,0.20))	(0.10,0.25,0.15))
C7	((0.95,0.90,0.95),	((0.35,0.35,0.10),	((0.60,0.45,0.50),	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.95,0.90,0.95),	((0.40,0.45,0.50),
	(0.10,0.10,0.05),	(0.50,0.75,0.80),	(0.20,0.15,0.25),	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.10,0.10,0.05),	(0.40,0.45,0.50),
	(0.05,0.05,0.05))	(0.50,0.75,0.65))	(0.10,0.25,0.15))	(0.05,0.05,0.05))	(0.45,0.80,0.70))	(0.05,0.05,0.05))	(0.35,0.40,0.45))
C <sub>8</sub>	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.35,0.35,0.10),	((0.95,0.90,0.95),	((0.50,0.30,0.50),
	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.50,0.75,0.80),	(0.10,0.10,0.05),	(0.50,0.35,0.45),
C <sub>9</sub>	(0.05,0.05,0.05))	(0.45,0.80,0.70))	(0.10,0.15,0.20)) ((0.95,0.90,0.95),	(0.05,0.05,0.05))	(0.50,0.75,0.65)) ((0.50,0.30,0.50),	(0.05,0.05,0.05)) ((0.20,0.20,0.10),	(0.45,0.30,0.60)) ((0.35,0.35,0.10),
<u>_</u> 9	((0.20,0.20,0.10), (0.65,0.80,0.85),	((0.95,0.90,0.95), (0.10,0.10,0.05),	(0.95,0.90,0.95),	(0.70,0.75,0.80), (0.15,0.20,0.25),	(0.50,0.35,0.45),	(0.20,0.20,0.10), (0.65,0.80,0.85),	(0.50,0.75,0.80),
	(0.45,0.80,0.70))	(0.05,0.05,0.05))	(0.05,0.05,0.05))	(0.10,0.15,0.20))	(0.45,0.30,0.60))	(0.45,0.80,0.70))	(0.50,0.75,0.65))
C <sub>10</sub>	((0.35,0.35,0.10),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.60,0.45,0.50),	((0.40,0.45,0.50),	((0.35,0.35,0.10),	((0.20,0.20,0.10),
CIO	(0.50,0.75,0.80),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.20,0.15,0.25),	(0.40,0.45,0.50),	(0.50,0.75,0.80),	(0.65,0.80,0.85),
	(0.50,0.75,0.65))	(0.05,0.05,0.05))	(0.05,0.05,0.05))	(0.10,0.25,0.15))	(0.35,0.40,0.45))	(0.50,0.75,0.65))	(0.45,0.80,0.70))
C <sub>11</sub>	((0.50,0.30,0.50),	((0.70,0.75,0.80),	((0.20,0.20,0.10),	((0.40,0.45,0.50),	((0.95,0.90,0.95),	((0.50,0.30,0.50),	((0.95,0.90,0.95),
	(0.50,0.35,0.45),	(0.15,0.20,0.25),	(0.65,0.80,0.85),	(0.40,0.45,0.50),	(0.10,0.10,0.05),	(0.50,0.35,0.45),	(0.10,0.10,0.05),
	(0.45,0.30,0.60))	(0.10,0.15,0.20))	(0.45,0.80,0.70))	(0.35,0.40,0.45))	(0.05,0.05,0.05))	(0.45,0.30,0.60))	(0.05,0.05,0.05))
C <sub>12</sub>	((0.40,0.45,0.50),	((0.60,0.45,0.50),	((0.35,0.35,0.10),	((0.50,0.30,0.50),	((0.95,0.90,0.95),	((0.40,0.45,0.50),	((0.95,0.90,0.95),
	(0.40,0.45,0.50),	(0.20,0.15,0.25),	(0.50,0.75,0.80),	(0.50,0.35,0.45),	(0.10,0.10,0.05),	(0.40,0.45,0.50),	(0.10,0.10,0.05),
	(0.35, 0.40, 0.45))	(0.10,0.25,0.15))	(0.50,0.75,0.65))	(0.45, 0.30, 0.60))	(0.05, 0.05, 0.05))	(0.35, 0.40, 0.45))	(0.05, 0.05, 0.05))
C <sub>13</sub>	((0.60, 0.45, 0.50),	((0.40,0.45,0.50),	((0.50,0.30,0.50),	((0.35,0.35,0.10),	((0.20,0.20,0.10),	((0.60,0.45,0.50),	((0.70,0.75,0.80),
	(0.20, 0.15, 0.25),	(0.40,0.45,0.50),	(0.50, 0.35, 0.45),	(0.50,0.75,0.80),	(0.65,0.80,0.85),	(0.20,0.15,0.25),	(0.15,0.20,0.25),
	(0.10,0.25,0.15))	(0.35,0.40,0.45))	(0.45,0.30,0.60))	(0.50,0.75,0.65))	(0.45,0.80,0.70))	(0.10,0.25,0.15))	(0.10,0.15,0.20))
$C_{14}$	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.35,0.35,0.10),	((0.70,0.75,0.80),	((0.40,0.45,0.50),
	(0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.50,0.75,0.80),	(0.15,0.20,0.25),	(0.40,0.45,0.50),
	(0.10,0.15,0.20))	(0.05,0.05,0.05))	(0.05,0.05,0.05))	(0.45,0.80,0.70))	(0.50,0.75,0.65))	(0.10,0.15,0.20))	(0.35,0.40,0.45))
	A <sub>1</sub>	A <sub>2</sub>	A3	A <sub>4</sub>	A <sub>5</sub>	A <sub>6</sub>	A <sub>7</sub>
$C_1$	((0.20,0.20,0.10),	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.60,0.45,0.50),	((0.40,0.45,0.50),
	(0.65,0.80,0.85),	(0.15,0.20,0.25), (0.10,0.15,0.20))	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.20,0.15,0.25),	(0.40,0.45,0.50),
C <sub>2</sub>	(0.45,0.80,0.70))	, , , , , , , , , , , , , , , , , , , ,	(0.05,0.05,0.05))	(0.05,0.05,0.05)) ((0.70,0.75,0.80),	(0.45,0.80,0.70)) ((0.95,0.90,0.95),	(0.10,0.25,0.15)) ((0.95,0.90,0.95),	(0.35,0.40,0.45))
C2	((0.35,0.35,0.10), (0.50,0.75,0.80),	((0.70,0.75,0.80), (0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	((0.20,0.20,0.10), (0.65,0.80,0.85),
	(0.50,0.75,0.65))	(0.10,0.15,0.20))	(0.05,0.05,0.05))	(0.10,0.15,0.20))	(0.05,0.05,0.05))	(0.05,0.05,0.05))	(0.45,0.80,0.70))
Сз	((0.50,0.30,0.50),	((0.70,0.75,0.80),	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.35,0.35,0.10),
	(0.50,0.35,0.45),	(0.15,0.20,0.25),	(0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.50,0.75,0.80),
	(0.45,0.30,0.60))	(0.10,0.15,0.20))	(0.10,0.15,0.20))	(0.05,0.05,0.05))	(0.05,0.05,0.05))	(0.45,0.80,0.70))	(0.50,0.75,0.65))
C <sub>4</sub>	((0.40,0.45,0.50),	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.40,0.45,0.50),	((0.20,0.20,0.10),
	(0.40,0.45,0.50),	(0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.40,0.45,0.50),	(0.65,0.80,0.85),
	(0.35,0.40,0.45))	(0.10,0.15,0.20))	(0.05,0.05,0.05))	(0.05,0.05,0.05))	(0.45,0.80,0.70))	(0.35,0.40,0.45))	(0.45,0.80,0.70))
C <sub>5</sub>	((0.60,0.45,0.50),	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.60,0.45,0.50),	((0.70,0.75,0.80),
	(0.20,0.15,0.25),	(0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.20,0.15,0.25),	(0.15,0.20,0.25),
<u> </u>	(0.10,0.25,0.15))	(0.10,0.15,0.20))	(0.05,0.05,0.05))	(0.05,0.05,0.05))	(0.45,0.80,0.70))	(0.10,0.25,0.15))	(0.10,0.15,0.20))
C <sub>6</sub>	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.95,0.90,0.95),	((0.70,0.75,0.80),	((0.60,0.45,0.50),
	(0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.65, 0.80, 0.85),	(0.10,0.10,0.05),	(0.15,0.20,0.25),	(0.20,0.15,0.25),
	(0.10,0.15,0.20))	(0.05,0.05,0.05))	(0.05,0.05,0.05))	(0.45,0.80,0.70))	(0.05,0.05,0.05))	(0.10,0.15,0.20))	(0.10,0.25,0.15))
<b>C</b> <sub>7</sub>	((0.95,0.90,0.95),	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.95,0.90,0.95),	((0.40,0.45,0.50),
	(0.10,0.10,0.05),	(0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.10,0.10,0.05),	(0.40,0.45,0.50),
	(0.05,0.05,0.05))	(0.10,0.15,0.20))	(0.05,0.05,0.05))	(0.05,0.05,0.05))	(0.45,0.80,0.70))	(0.05,0.05,0.05))	(0.35,0.40,0.45))
C <sub>8</sub>	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.20,0.20,0.10),	((0.50,0.30,0.50),
	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.15,0.20,0.25),	(0.10,0.10,0.05),	(0.10,0.10,0.05),	(0.65,0.80,0.85),	(0.50,0.35,0.45),
	(0 0E 0 0E 0 0E))	(0.45,0.80,0.70))	(0.10, 0.15, 0.20))	(0.05, 0.05, 0.05))	(0.05, 0.05, 0.05))	(0.45, 0.80, 0.70))	(0.45,0.30,0.60))
	(0.05,0.05,0.05))	, ,,,		. ,,		, ,,	
C <sub>9</sub>	((0.20,0.20,0.10),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.70,0.75,0.80),	((0.95,0.90,0.95),	((0.95,0.90,0.95),	((0.20,0.20,0.10),
C <sub>9</sub>		, ,,,		. ,,	((0.95,0.90,0.95), (0.10,0.10,0.05), (0.05,0.05,0.05))	, ,,	((0.20,0.20,0.10), (0.65,0.80,0.85), (0.45,0.80,0.70))

((0.35, 0.35, 0.10),((0.95,0.90,0.95), ((0.70, 0.75, 0.80),((0.95,0.90,0.95), ((0.95, 0.90, 0.95),((0.20,0.20,0.10),((0.20, 0.20, 0.10),(0.50, 0.75, 0.80),(0.15, 0.20, 0.25),(0.10, 0.10, 0.05),(0.65, 0.80, 0.85),(0.65, 0.80, 0.85),(0.10,0.10,0.05). (0.10,0.10,0.05). (0.50, 0.75, 0.65))(0.05, 0.05, 0.05))(0.10, 0.15, 0.20))(0.05, 0.05, 0.05))(0.05, 0.05, 0.05))(0.45, 0.80, 0.70))(0.45, 0.80, 0.70))((0.20,0.20,0.10), ((0.95,0.90,0.95), C<sub>11</sub> ((0.95,0.90,0.95), ((0.20, 0.20, 0.10),((0.50,0.30,0.50),((0.70, 0.75, 0.80),((0.70, 0.75, 0.80),(0.65, 0.80, 0.85),(0.15, 0.20, 0.25),(0.10, 0.10, 0.05),(0.10, 0.10, 0.05),(0.65, 0.80, 0.85),(0.50, 0.35, 0.45),(0.15, 0.20, 0.25),(0.05, 0.05, 0.05))(0.45, 0.30, 0.60))(0.10, 0.15, 0.20))(0.45, 0.80, 0.70))(0.10, 0.15, 0.20))(0.05, 0.05, 0.05))(0.45, 0.80, 0.70))((0.95,0.90,0.95), ((0.70, 0.75, 0.80),((0.95, 0.90, 0.95), $C_{12}$ ((0.40, 0.45, 0.50),((0.60, 0.45, 0.50),((0.95, 0.90, 0.95),((0.20,0.20,0.10),(0.40, 0.45, 0.50),(0.20, 0.15, 0.25), (0.15, 0.20, 0.25),(0.10, 0.10, 0.05),(0.10, 0.10, 0.05),(0.65, 0.80, 0.85),(0.10, 0.10, 0.05), $(0.10, \underline{0.25}, \underline{0.15}))$ (0.35, 0.40, 0.45))(0.10, 0.15, 0.20))(0.05, 0.05, 0.05))(0.05, 0.05, 0.05))(0.45, 0.80, 0.70))(0.05, 0.05, 0.05))((0.60, 0.45, 0.50),((0.70,0.75,0.80). ((0.95, 0.90, 0.95),((0.95,0.90,0.95), ((0.20, 0.20, 0.10),((0.60, 0.45, 0.50),((0.70,0.75,0.80), (0.20, 0.15, 0.25),(0.15, 0.20, 0.25),(0.10, 0.10, 0.05),(0.10, 0.10, 0.05),(0.65, 0.80, 0.85),(0.20, 0.15, 0.25),(0.15, 0.20, 0.25),(0.10, 0.25, 0.15))(0.10, 0.15, 0.20))(0.05, 0.05, 0.05)(0.05, 0.05, 0.05))(0.45, 0.80, 0.70))(0.10, 0.25, 0.15))(0.10, 0.15, 0.20))((0.70, 0.75, 0.80),((0.95, 0.90, 0.95),((0.95, 0.90, 0.95),((0.20, 0.20, 0.10), ((0.35, 0.35, 0.10),((0.70, 0.75, 0.80),((0.40, 0.45, 0.50),(0.15, 0.20, 0.25),(0.10, 0.10, 0.05),(0.10, 0.10, 0.05),(0.65, 0.80, 0.85),(0.50, 0.75, 0.80), (0.15, 0.20, 0.25),(0.40, 0.45, 0.50),(0.10, 0.15, 0.20))(0.05, 0.05, 0.05)(0.05, 0.05, 0.05)(0.45, 0.80, 0.70))(0.50, 0.75, 0.65))(0.10, 0.15, 0.20))(0.35, 0.40, 0.45)) $A_2$ Аз  $A_4$  $A_5$  $A_6$ A7  $A_1$  $C_1$ ((0.70, 0.75, 0.80),((0.50, 0.30, 0.50),((0.40, 0.45, 0.50),((0.20, 0.20, 0.10), ((0.70, 0.75, 0.80),((0.60, 0.45, 0.50),((0.40, 0.45, 0.50),(0.15, 0.20, 0.25),(0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65.0.80.0.85). (0.15, 0.20, 0.25),(0.20, 0.15, 0.25),(0.40, 0.45, 0.50).(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.10, 0.15, 0.20))(0.10, 0.25, 0.15))(0.35, 0.40, 0.45)) $C_2$ ((0.35, 0.35, 0.10),((0.70, 0.75, 0.80),((0.50, 0.30, 0.50),((0.40, 0.45, 0.50),((0.20, 0.20, 0.10),((0.35, 0.35, 0.10),((0.50, 0.30, 0.50),(0.50,0.75,0.80), (0.50, 0.35, 0.45),(0.65, 0.80, 0.85),(0.50, 0.75, 0.80),(0.50, 0.35, 0.45),(0.15, 0.20, 0.25)(0.40, 0.45, 0.50). (0.50, 0.75, 0.65))(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.50, 0.75, 0.65))(0.45, 0.30, 0.60)) $C_3$ ((0.50, 0.30, 0.50),((0.70, 0.75, 0.80),((0.70, 0.75, 0.80),((0.50, 0.30, 0.50), ((0.40, 0.45, 0.50), ((0.20, 0.20, 0.10),((0.35, 0.35, 0.10),(0.50, 0.35, 0.45),(0.15, 0.20, 0.25),(0.15, 0.20, 0.25),(0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65, 0.80, 0.85),(0.50, 0.75, 0.80), (0.45, 0.30, 0.60))(0.10, 0.15, 0.20))(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.50, 0.75, 0.65)) $C_4$ ((0.70, 0.75, 0.80),((0.50, 0.30, 0.50), ((0.20, 0.20, 0.10),((0.20, 0.20, 0.10),((0.40, 0.45, 0.50),((0.60, 0.45, 0.50),((0.40, 0.45, 0.50),(0.40, 0.45, 0.50),(0.20, 0.15, 0.25),(0.15, 0.20, 0.25),(0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65, 0.80, 0.85),(0.65, 0.80, 0.85),(0.35, 0.40, 0.45))(0.10, 0.25, 0.15))(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.45, 0.80, 0.70)) $C_5$ ((0.60, 0.45, 0.50), ((0.20,0.20,0.10), ((0.60, 0.45, 0.50), ((0.70,0.75,0.80), ((0.50, 0.30, 0.50),((0.40, 0.45, 0.50),((0.70, 0.75, 0.80),(0.20, 0.15, 0.25),(0.15, 0.20, 0.25),(0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65, 0.80, 0.85),(0.20, 0.15, 0.25),(0.15, 0.20, 0.25),(0.10, 0.25, 0.15))(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.10, 0.25, 0.15))(0.10, 0.15, 0.20))((0.70,0.75,0.80), ((0.70, 0.75, 0.80),((0.50, 0.30, 0.50),((0.40, 0.45, 0.50),((0.20, 0.20, 0.10), ((0.95, 0.90, 0.95),((0.60, 0.45, 0.50),(0.20,0.15,0.25), (0.15, 0.20, 0.25), (0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65, 0.80, 0.85), (0.10, 0.10, 0.05), (0.15, 0.20, 0.25), (0.05, 0.05, 0.05))(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.10, 0.15, 0.20))(0.10, 0.25, 0.15))**C**7 ((0.95,0.90,0.95), ((0.20, 0.20, 0.10),((0.40, 0.45, 0.50),((0.35, 0.35, 0.10),((0.70, 0.75, 0.80),((0.50, 0.30, 0.50),((0.40, 0.45, 0.50),(0.10, 0.10, 0.05),(0.50, 0.75, 0.80), (0.15, 0.20, 0.25),(0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65, 0.80, 0.85),(0.40, 0.45, 0.50),(0.05, 0.05, 0.05))(0.50, 0.75, 0.65))(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.35, 0.40, 0.45)) $C_8$ ((0.70,0.75,0.80), ((0.50, 0.30, 0.50),((0.40, 0.45, 0.50),((0.20,0.20,0.10), ((0.35, 0.35, 0.10), ((0.95,0.90,0.95), ((0.50, 0.30, 0.50),(0.15, 0.20, 0.25),(0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65, 0.80, 0.85),(0.50, 0.75, 0.80),(0.10, 0.10, 0.05),(0.50, 0.35, 0.45),(0.50, 0.75, 0.65))(0.05, 0.05, 0.05)(0.10.0.15.0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.45, 0.30, 0.60))((0.20, 0.20, 0.10),((0.70, 0.75, 0.80),((0.50, 0.30, 0.50),((0.40, 0.45, 0.50), ((0.20, 0.20, 0.10),((0.20,0.20,0.10),((0.35, 0.35, 0.10),(0.65, 0.80, 0.85),(0.15, 0.20, 0.25), (0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65, 0.80, 0.85),(0.65, 0.80, 0.85),(0.50, 0.75, 0.80), (0.45, 0.80, 0.70))(0.45, 0.80, 0.70))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.50, 0.75, 0.65))(0.45, 0.80, 0.70))(0.10, 0.15, 0.20))((0.35, 0.35, 0.10),((0.95, 0.90, 0.95),((0.70, 0.75, 0.80),((0.50, 0.30, 0.50), ((0.40, 0.45, 0.50),((0.20, 0.20, 0.10),((0.20, 0.20, 0.10),(0.50, 0.75, 0.80), (0.10, 0.10, 0.05),(0.15, 0.20, 0.25), (0.50, 0.35, 0.45), (0.40, 0.45, 0.50), (0.65, 0.80, 0.85),(0.65, 0.80, 0.85),(0.50, 0.75, 0.65))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.45, 0.80, 0.70))(0.05, 0.05, 0.05))(0.10.0.15.0.20) $C_{11}$ ((0.50, 0.30, 0.50),((0.70, 0.75, 0.80),((0.50, 0.30, 0.50),((0.40, 0.45, 0.50),((0.20, 0.20, 0.10),((0.50,0.30,0.50),((0.95, 0.90, 0.95),(0.50, 0.35, 0.45),(0.15, 0.20, 0.25),(0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65, 0.80, 0.85),(0.50, 0.35, 0.45),(0.10, 0.10, 0.05),(0.45, 0.30, 0.60))(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.45, 0.30, 0.60))(0.05, 0.05, 0.05) $C_{12}$ ((0.40, 0.45, 0.50),((0.70,0.75,0.80). ((0.50,0.30,0.50),((0.40, 0.45, 0.50),((0.20.0.20.0.10).((0.95, 0.90, 0.95),((0.95,0.90,0.95), (0.15, 0.20, 0.25),(0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65, 0.80, 0.85),(0.10, 0.10, 0.05),(0.40, 0.45, 0.50),(0.10, 0.10, 0.05),(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.05, 0.05, 0.05))(0.35, 0.40, 0.45))(0.05, 0.05, 0.05))((0.70,0.75,0.80), ((0.20,0.20,0.10), ((0.60, 0.45, 0.50), ((0.50, 0.30, 0.50),((0.40, 0.45, 0.50), ((0.60, 0.45, 0.50),((0.70,0.75,0.80), (0.20, 0.15, 0.25),(0.15, 0.20, 0.25), (0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.65, 0.80, 0.85),(0.20, 0.15, 0.25), (0.15, 0.20, 0.25),(0.10, 0.25, 0.15))(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.10, 0.25, 0.15))(0.10, 0.15, 0.20)) $C_{14}$ ((0.70,0.75,0.80), ((0.50, 0.30, 0.50),((0.40, 0.45, 0.50),((0.20, 0.20, 0.10), ((0.35, 0.35, 0.10), ((0.70,0.75,0.80), ((0.40, 0.45, 0.50),(0.15, 0.20, 0.25),(0.65, 0.80, 0.85),(0.50, 0.75, 0.80), (0.15, 0.20, 0.25),(0.50, 0.35, 0.45),(0.40, 0.45, 0.50),(0.40, 0.45, 0.50)(0.10, 0.15, 0.20))(0.45, 0.30, 0.60))(0.35, 0.40, 0.45))(0.45, 0.80, 0.70))(0.50, 0.75, 0.65))(0.10, 0.15, 0.20))(0.35, 0.40, 0.45))

Table 3. The normalized decision matrix by the Entropy method.

		<b>A</b> 1	$A_2$	<b>A</b> 3	$A_4$	<b>A</b> 5	$A_6$	A <sub>7</sub>
ĺ	$C_1$	0.098933	0.121242	0.18558	0.162625	0.14258	0.164888	0.124151
ĺ	$C_2$	0.075768	0.196587	0.195222	0.185324	0.115017	0.126621	0.105461

<b>C</b> <sub>3</sub>	0.132399	0.201751	0.154466	0.167075	0.182487	0.084063	0.077758
$C_4$	0.140095	0.19409	0.178402	0.173294	0.137541	0.114192	0.062386
<b>C</b> 5	0.152466	0.153064	0.142003	0.127055	0.100747	0.152466	0.172197
$C_6$	0.166667	0.137442	0.1386	0.049479	0.193576	0.166667	0.147569
<b>C</b> <sub>7</sub>	0.203035	0.103187	0.177542	0.173596	0.073445	0.152656	0.11654
$C_8$	0.202862	0.076312	0.162798	0.159936	0.117965	0.159936	0.120191
C <sub>9</sub>	0.06019	0.224569	0.201338	0.180218	0.142907	0.11862	0.072158
$C_{10}$	0.077758	0.234326	0.212609	0.181786	0.167776	0.065849	0.059895
C <sub>11</sub>	0.121037	0.184438	0.076849	0.143452	0.161063	0.152097	0.161063
C <sub>12</sub>	0.133135	0.138484	0.117088	0.120654	0.198811	0.093016	0.198811
C <sub>13</sub>	0.160428	0.161057	0.149418	0.13369	0.053791	0.160428	0.181189
$C_{14}$	0.187317	0.186016	0.186667	0.05561	0.072195	0.187317	0.124878

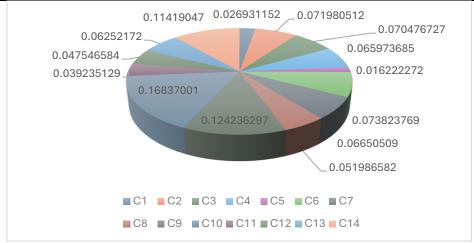


Figure 3. The criteria weights.

#### 4.2 Results T2NSs-MOOSRA Method

In step 5, Equation (10) is used to normalize the decision matrix, ensuring that all criteria values are standardized for effective comparison, as illustrated in Table 4. Next, in step 6, Equation (11) computes the weighted normalized decision matrix by incorporating the relative importance of each criterion, with the resulting values presented in Table 5. Finally, in step 7, Equation (12) is applied to rank the alternatives based on these weighted values, and the final rankings are displayed in Table 6.

					,		
	<b>A</b> 1	$A_2$	<b>A</b> 3	$A_4$	<b>A</b> 5	$A_6$	A <sub>7</sub>
$C_1$	0.155288	0.190304	0.291292	0.255261	0.223797	0.258813	0.194871
$C_2$	0.118419	0.307249	0.305115	0.289646	0.179762	0.197898	0.164826
<b>C</b> <sub>3</sub>	0.21346	0.325272	0.249036	0.269366	0.294213	0.13553	0.125365
$C_4$	0.237411	0.328913	0.302327	0.293672	0.233083	0.193514	0.105722
<b>C</b> 5	0.224733	0.225614	0.20931	0.187277	0.1485	0.224733	0.253816
$C_6$	0.223506	0.184315	0.185867	0.066353	0.259593	0.223506	0.197896
<b>C</b> <sub>7</sub>	0.284748	0.144715	0.248995	0.243462	0.103003	0.214093	0.163443
$C_8$	0.303542	0.114185	0.243595	0.239313	0.176511	0.239313	0.179842

Table 4. The normalized decision matrix by the MOOSRA method.

<b>C</b> 9	0.091468	0.341267	0.305963	0.273869	0.21717	0.180262	0.109655
$C_{10}$	0.111879	0.33715	0.305905	0.261556	0.241397	0.094745	0.086177
C <sub>11</sub>	0.185825	0.283161	0.117984	0.220237	0.247275	0.23351	0.247275
$C_{12}$	0.186341	0.193828	0.16388	0.168871	0.278263	0.130189	0.278263
C <sub>13</sub>	0.236963	0.237892	0.220701	0.197469	0.079452	0.236963	0.267628
$C_{14}$	0.26822	0.266357	0.267289	0.079628	0.103376	0.26822	0.178813

Table 5. The weighted normalized decision matrix by the MOOSRA method.

	<b>A</b> 1	$A_2$	<b>A</b> 3	$A_4$	<b>A</b> 5	$A_6$	A <sub>7</sub>
$C_1$	0.004182	0.005125	0.007845	0.006874	0.006027	0.00697	0.005248
$C_2$	0.008524	0.022116	0.021962	0.020849	0.012939	0.014245	0.011864
<b>C</b> <sub>3</sub>	0.015044	0.022924	0.017551	0.018984	0.020735	0.009552	0.008835
$C_4$	0.015663	0.0217	0.019946	0.019375	0.015377	0.012767	0.006975
<b>C</b> 5	0.003646	0.00366	0.003395	0.003038	0.002409	0.003646	0.004117
$C_6$	0.0165	0.013607	0.013721	0.004898	0.019164	0.0165	0.014609
<b>C</b> <sub>7</sub>	0.018937	0.009624	0.016559	0.016191	0.00685	0.014238	0.01087
C <sub>8</sub>	0.01578	0.005936	0.012664	0.012441	0.009176	0.012441	0.009349
C <sub>9</sub>	0.011364	0.042398	0.038012	0.034025	0.02698	0.022395	0.013623
$C_{10}$	0.018837	0.056766	0.051505	0.044038	0.040644	0.015952	0.01451
$C_{11}$	0.007291	0.01111	0.004629	0.008641	0.009702	0.009162	0.009702
C <sub>12</sub>	0.00886	0.009216	0.007792	0.008029	0.01323	0.00619	0.01323
$C_{13}$	0.014815	0.014873	0.013799	0.012346	0.004967	0.014815	0.016733
$C_{14}$	0.030628	0.030415	0.030522	0.009093	0.011805	0.030628	0.020419

Table 6. The rank of alternatives.

	Values	Rank
$A_1$	0.190071	3
$A_2$	0.26947	6
<b>A</b> 3	0.259903	5
$A_4$	0.218823	4
$A_5$	0.200007	3
$A_6$	0.189501	2
<b>A</b> <sub>7</sub>	0.160085	1

## 5. Sensitivity analysis

A sensitivity analysis was conducted to assess how changes in criteria weights affect the ranking of alternatives. The study examined fifteen different weighting scenarios, as illustrated in Figure 4. In the first scenario, equal weights were assigned to all criteria. In the second scenario, the weight of the first criterion was increased by 10%, while the weights of the other criteria remained unchanged. Similarly, in the third scenario, a 10% increase was applied to the weight of the second criterion, with the other criteria maintaining their original values. The MOOSRA method was then applied to each of the fifteen cases to determine the rankings of the alternatives. For every case, both the normalized decision matrix and the weighted normalized decision matrix were

computed before ranking the alternatives. Figure 5 displays the rankings across these cases, consistently showing that alternative 2 ranks as the best option while alternative 7 ranks as the worst. Overall, the results indicate that the ranking of alternatives remains stable despite the variations in criteria weights.

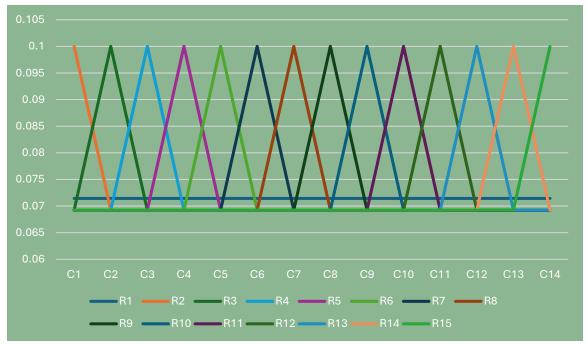


Figure 4. The criteria weights with different cases.

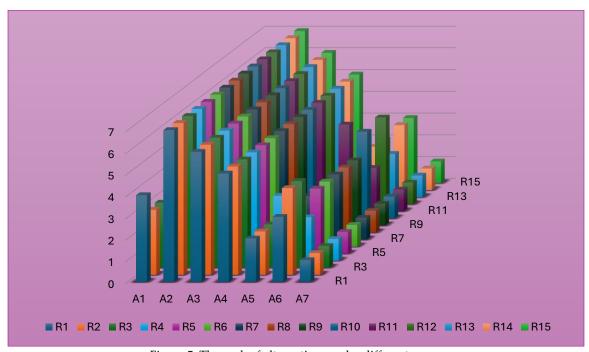


Figure 5. The rank of alternatives under different cases.

#### 6. Conclusions

This study has made several significant contributions. First, it introduced distinct definitions and operations for type-2 neutrosophic sets to effectively handle uncertainty and vague data. Second, the research applied various Multi-Criteria Decision-Making (MCDM) methods, such as the Entropy and MOOSRA methods, to calculate criteria weights and rank the alternatives. Third, a detailed case study was conducted to identify the best project based on art design and different courses. Fourth, a sensitivity analysis was performed to examine the ranking of alternatives under various criteria weight scenarios, demonstrating that the rankings remain stable regardless of the changes. Looking ahead, future research will investigate additional techniques for type-2 neutrosophic sets, including the CRITIC method, correlation coefficient, and similarity metrics. This study is the first of its kind in the field to rank art design projects using these innovative approaches.

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