FERMATEAN NEUTROSOPHIC DECISION-MAKING METHODOLOGY IN SUPPLIER SELECTION OF THREE-DIMENSIONAL (3D) PRINTERS

Thesis submitted in
Partial Fulfillment of the Requirements for the
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Signature of the Director

Signature of the Supervisor

DECLARATION

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I declare that the thesis " **Fermatean Neutrosophic Decision Making Methodology in Supplier Selection of Three-Dimensional (3d) Printers**" submitted by me for the degree of **Master of Science (M.Sc.)** is the record of work carried out during the period from December 2024 to April 2025 under the guidance of **Dr. C. Antony Crispin Sweety, M.Sc., B.Ed., M.Phil., Ph.D.**, Assistant Professor, Department of Mathematics, Avinashilingam Institute for Home Science and Higher Education for women, Coimbatore, and has not formed the basis for the award of any Degree, Diploma, Associateship, Fellowship, Titles in this institute or any other University or other similar institution of Higher Learning.

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Signature of the Candidate

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ABSTRACT

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In the rapidly evolving landscape of additive manufacturing, the selection of appropriate three-dimensional (3D) printer suppliers plays a critical role in ensuring quality, reliability, and efficiency in production, particularly in high-precision industries such as aerospace, healthcare, and automotive. Traditional decision-making methods often fall short of addressing the inherent uncertainty and ambiguity present in expert evaluations. To overcome these limitations, this study presents a robust decision-making framework based on Fermatean Neutrosophic Sets (FNS), integrating Fermatean Neutrosophic Analytic Hierarchy Process (FN-AHP) with Fermatean Neutrosophic VIKOR (FN-VIKOR). The FN-AHP is employed to derive precise criteria weights by accommodating hesitancy, vagueness, and incomplete information, while FN-VIKOR facilitates the ranking and selection of optimal suppliers based on compromise solutions. A real-world case study involving multiple 3D printer suppliers is used to demonstrate the practical applicability of the proposed method. Comparative analysis with the Interval-Valued Pythagorean Fuzzy AHP (IVPF-AHP) integrated VIKOR approach confirms the reliability and consistency of the FN-based framework. The results not only validate the robustness of the Fermatean Neutrosophic methodology but also highlight its superior capacity to support strategic procurement decisions under uncertainty.

CONTENT

CONTENT

CHAPTER 1

CHAPTER 1

1.1 INTRODUCTION

In recent years, additive manufacturing, more commonly known as Three-dimensional (3D) printing, has revolutionized the industrial landscape. From prototyping and tooling to end-use production, 3D printing is being adopted across multiple sectors including aerospace, automotive, healthcare, and electronics increasingly adopt 3D printing technologies, the selection of reliable and efficient 3D printer suppliers has become a strategic imperative. However, this selection process is inherently complex, involving multiple conflicting criteria such as Cost (C), Benefit (B), Accessibility to Technology (A), Logistics Support (L), and Technical Service (T). Moreover, Judgments in this context are often fraught with uncertainty, imprecision, and hesitancy due to the rapidly changing technological landscape and varying levels of supplier performance.

In the competitive environment that develops in parallel with the developing technology in the business world, business offers their products and services by using their resources effectively to always be ahead of their competitors in the sector and to continue their existence for a long time. Choosing the most suitable supplier with minimum cost, in the fastest time, and at the right time provides benefits in terms of increasing its profitability in line with increasing its competitive power.

Multi-Criteria Decision-Making (MCDM) methods are divided into two categories: Multiple Attribute Decision Making (MADM) and Multiple Objective Decision Making (MODM). The MADM method is referred to as discrete MCDM, while MODM is called continuous MCDM.

The MADM method has many types such as

- Analytic Hierarchy Process (AHP),
- Technique for Order Preference by Similarity to Ideal Solution (TOPSIS),
- Analytic Network Process (ANP),
- Gray Relation Analysis (GRA),
- Vise Kriterijumska Optimizacijia I Kompromisno Resenje (VIKOR),

- Multi-Objective Optimization by Ratio Analysis (MOORA),
- Best-Worst Method (BWM).

The goal of MADM methods is to model decision processes based on criteria, maximizing the utility that decision-makers will obtain at the end of the process. MADM methods are designed to determine the best alternative, classify alternatives into a few categories, and/or rank alternatives according to subjective preference order. There are many methods suggested for this purpose. In this supplier selection Multi-Criteria Decision-Making (MCDM) techniques, such as the Analytic Hierarchy Process (AHP) and VIKOR, have been used for supplier evaluation. However, these methods may not fully capture the nuances of human reasoning under uncertainty. To address this challenge, researchers have explored fuzzy set theories, including Intuitionistic Fuzzy Sets, Pythagorean Fuzzy Sets, etc, Nevertheless, these frameworks remain limited in their ability to express higher degrees of uncertainty and hesitancy inherent in expert assessments.

Fermatean Neutrosophic Sets (FNS), a recent extension of Neutrosophic theory, provide a powerful mathematical tool for modeling uncertainty, incorporating truth, falsity, and indeterminacy degrees with greater flexibility through the constraint $\mathrm{T}^3 + \mathrm{I}^3 + \mathrm{F}^3 \leq 2$. This higher-order formulation allows for a more realistic and refined representation of human judgment, especially when decision-makers face ambiguous or incomplete information. By leveraging the strengths of FNS, this study proposes an integrated Fermatean Neutrosophic Decision-Making methodology combining FN-AHP and FN-VIKOR to address the complexities in 3D printer supplier selection.

The main objectives of this study are to

- Develop a structured decision-making model that effectively captures uncertainty and hesitancy in expert evaluations,
- Evaluate and rank potential 3D printer suppliers using the integrated FN-AHP and FN-VIKOR approach, and
- Compare the results with those obtained from traditional fuzzy-based models to demonstrate the efficacy and reliability of the proposed methodology.

This research aims to contribute to the growing body of knowledge in fuzzy MCDM and support practitioners in making more informed and confident supplier selection decisions in technologically dynamic environments.

1.1.1 ABBREVIATIONS

Three-Dimensional	3D
Fermatean Neutrosophic sets	FNS
Interval-Valued Pythagorean Fuzzy	IVPF
Analytic Hierarchy Process	AHP
Vise Kriterijumska Optimizacijia I Kompromisno Resenje	VIKOR
Fermatean Neutrosophic Analytic Hierarchy Process	FN-AHP
Interval-Valued Pythagorean Fuzzy Analytic Hierarchy Process	IVPF-AHP
Fermatean Neutrosophic Vise Kriterijumska Optimizacijia I Kompromisno Resenje	FN- VIKOR
Interval-Valued Pythagorean Fuzzy Vise Kriterijumska Optimizacijia I Kompromisno Resenje	IVPF-VIKOR
Multi-Criteria Decision-Making	MCDM
Multi-Attribute Decision-Making	MADM
Multi-Objective Decision-Making	MODM

1.2 REVIEW OF LITERATURE

The Fuzzy Set Theory (FST) was first introduced to the literature by **Zadeh** (1965) to handle imprecise, uncertain, and vague information in real-life decision-making processes. In a classical fuzzy set (FS), each element is characterized by a single membership function, where the membership degree ranges between 0 and 1. However, in complex situations, decision-makers often hesitate or remain uncertain while evaluating options. To handle such uncertainty, Intuitionistic Fuzzy Sets (IFSs) were proposed by **Atanassov** (1986) which introduced both membership and non-membership degrees, with the additional constraint that their sum cannot exceed 1.

Despite the advantages of PFSs, they still do not fully represent the indeterminacy in expert opinions. To overcome this limitation, Neutrosophic Set Theory (NST) was introduced by **Smarandache** (1998), which considers three components: truth (T), indeterminacy (I), and falsity (F). Each of these components is independently defined within the real subset of $[0^-, 1^+]$ allowing for greater flexibility in modeling inconsistent, incomplete, and indeterminate information. To simplify real-life applications of neutrosophic sets, Single-Valued Neutrosophic Sets (SVNSs) and Interval-Valued Neutrosophic Sets (IVNSs) were proposed. These sets allow for the representation of expert evaluations with more granularity and tolerance for uncertainty.

To provide more flexibility than IFSs, Pythagorean Fuzzy Sets (PFSs) were developed by **Yager** (2013), where the sum of the squares of the membership and non-membership degrees should not exceed 1. This extension allows decision-makers to reflect more hesitation and better represent the real-world complexity in decision environments. Owing to their capability to handle vagueness and hesitation more effectively, PFSs have been widely used in various multi-criteria decision-making (MCDM) applications.

However, even these extensions sometimes fall short in highly complex scenarios. To further enhance the representation of uncertainty, Fermatean Neutrosophic Sets (FNSs) was introduced by **C. Antony et al** (2021). In FNSs, the cubic sum of the truth, indeterminacy, and falsity degrees is constrained such that: $\mathrm{T}^3 + \mathrm{I}^3 + \mathrm{F}^3 \leq 2$ This cubic relationship provides greater flexibility than Intuitionistic, Pythagorean, or regular Neutrosophic Sets, making FNSs more suitable for expressing hesitant, vague, and conflicting expert judgments. FNSs allow experts to express evaluations with high indeterminacy while maintaining logical consistency, which is crucial in decision-making environments with subjective or incomplete data.

Vise Kriterijumska Optimizacijia I Kompromisno Resenje (VIKOR) was introduced by **Opricovic and Tzeng** in 1998 to determine the alternative ranking based on the results of the regret (R) value of each alternative and Analytic Network Process (AHP) was introduced by **Saaty** in 1970 utilizes pairwise comparisons in order to do the ranking in Multi-Criteria Decision Making.

Fermatean Neutrosophic Set (FNS) is a flexible framework and generalized theory that includes fuzzy, Intuitionistic fuzzy, Pythagorean fuzzy, spherical fuzzy, Fermatean fuzzy sets, and Neutrosophic set theory.

1.3 BASIC CONCEPTS

In decision-making processes, it is often difficult for decision-makers to provide exact evaluations due to vague, incomplete, or indeterminate information. Fermatean Neutrosophic Sets (FNSs) are used to better handle such uncertainty. In FNSs, the truth, indeterminacy, and falsity membership functions are defined separately and follow a cubic constraint. This structure allows a more flexible and realistic representation of expert opinions under uncertainty. FNSs are effective in modeling complex, hesitant, and inconsistent evaluations in decision-making environments.

The FNSs can be expressed as follows:

Definition 1.3.1

Let X be a non-empty set. A **fuzzy set** A in X is characterized by its membership function $\mu_A: X \rightarrow [0,1]$ and $\mu_A(x)$ is interpreted as the degree of membership of element X in fuzzy set A, for each $x \in X$. A is completely determined by the set of tuples A={ $\left(x, \mu_A(x)\right)$: $x \in X$.

Definition 1.3.2.

The **Intuitionistic Fuzzy sets** defined on a non-empty set X as objects having the form $A=\{\langle x, \mu_A(x), v_A(x)\rangle : x \in X\}$, where the functions $\mu_A(x): X \rightarrow [0,1]$ and $v_A(x): X \rightarrow [0,1]$, denote the degree of membership and the degree of non-membership of each element $x \in X$ to the set A respectively, and $0 \leq \mu_A(x) + v_A(x) \leq 1$, for all $x \in X$. When $v_A(x) = 1 - \mu_A(x)$, for every $x \in X$, the set A becomes a fuzzy set.

Definition 1.3.3.

The **Pythagorean Fuzzy Sets** defined on a non-empty set X as the form P= $\left\{\langle x, \mu_P(x), v_P(x)\rangle : x \in X\right\}$, where the functions $\mu_P(x) : X \rightarrow [0,1]$ and $v_P(x) : X \rightarrow [0,1]$ denote the degree of membership and the degree of non-membership of each element $x \in X$ to the set P respectively, and $0 \leq \left(\mu_P(x)\right)^2 + \left(v_P(x)\right)^2 \leq 1$, for all $x \in X$. For any Pythagorean Fuzzy Set P and $x \in X$, $\pi_P(x) = \sqrt{1 - \left(\mu_P(x)\right)^2 - \left(v_P(x)\right)^2}$ is called the degree of indeterminacy of x to P.

Definition 1.3.4.

A **Fermatean fuzzy set** F in X is of the form $F = \{\langle x, \mu_F(x), v_F(x)\rangle : x \in X\}$, where $\mu_F(x) : X \to [0,1]$ and $v_F(x) : X \to [0,1]$, condition $0 \leq \left(\mu_F(x)\right)^3 + \left(v_F(x)\right)^3 \leq 1$, for all $x \in X$. $\mu_F(x)$ and $v_F(x)$ denotes, degree of membership function and degree of non membership function of the element x respectively in the set F.

For any FFS F and $x \in X$, $\pi_F(x) = \sqrt{1 - \left(\mu_F(x)\right)^3 - \left(v_F(x)\right)^3}$ is identified as the degree of indeterminacy of x to F.

Definition 1.3.5.

Let X be the universe. A **Neutrosophic set** (NS) A in X is characterized by the truth membership function T_A, an indeterminacy membership function I_A, and a falsity membership function F_A where T_A, I_A, and F_A are real standard elements 0f [0,1]. It can be written as

$$A = \{\langle x, \left(T_A(x), I_A(x), F_A(x)\right)\rangle : x \in E, T_A, I_A, F_A \in]^-0, 1^+[\}$$

There is no restriction on the sum of $T_A(x), I_A(x)$, and $F_A(x)$ so

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

Definition 1.3.6.

Let X be a non-empty set. A **Fermatean Neutrosophic set** A on X is defined as an object of the form:

$$C=\{\langle x,(T_C(x), I_C(x), F_C(x))\rangle \mid x \in X\},$$

Where $T_C(x)$, $I_C(x)$, and $F_C(x)$ represent the degrees of Truth membership function, indeterminacy membership function, and Falsity membership function respectively, with each component constrained within the interval [0,1]. Where T and F are dependent components, the following conditions hold for all $x \in X$.

$$0 \le I^3 \le 1$$

$$0 \le T^3 + F^3 \le 1$$

$$0 \le T^3 + I^3 + F^3 \le 2$$

Some basic operations on Fermatean Neutrosophic sets:

Let X be a non-empty set. Consider two FNSs A and B on X, defined by:

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

$$B=\{\langle x,(T_B(x), I_B(x), F_B(x))\rangle \mid x \in X\}.$$

Where T, I, and F are the membership functions with values in the interval [0,1]. Let λ be a positive real number. The operations on these FNSs are then defined as follows.

i. $A^C = \{\langle x, F_A(x), 1 - I_A(x), T_A(x)\rangle : x \epsilon X\}$

ii. $A \cup B = \{max(T_A, T_B), min(I_A, I_B), \min(F_A, F_B)\}$

iii. $A \cap B = \{min(T_A, T_B), max(I_A, I_B), \max(F_A, F_B)\}$

iv. $A \oplus B = (T_A, I_A, F_A) \oplus (T_B, I_B, F_B) = \left(\sqrt[3]{T_A^3 + T_B^3 - T_A^3 T_B^3}, I_A I_B, F_A F_B\right)$

v. $A \otimes B = (T_A, I_A, F_A) \otimes (T_B, I_B, F_B) = \left(T_A T_B, \sqrt[3]{I_A^3 + I_B^3 - I_A^3 I_B^3}, \sqrt[3]{F_A^3 + F_B^3 - F_A^3 F_B^3}\right)$

vi. $A \ominus B = (T_A, I_A, F_A) \ominus (T_B, I_B, F_B) = \left\{\left(\sqrt[3]{\frac{T_A^3 - T_B^3}{1 - T_B^3}}, \frac{I_A}{I_B}, \frac{F_A}{F_B}\right) \mid if\ T_A \ge T_B, I_A \le I_B, F_A \le F_B\right\}$

vii. $A \oslash B = (T_A, I_A, F_A) \oslash (T_B, I_B, F_B)$

$$= \left\{\left(\frac{T_A}{T_B}, \sqrt[3]{\frac{I_A^3 - I_B^3}{1 - I_B^3}}, \sqrt[3]{\frac{F_A^3 - F_B^3}{1 - F_B^3}}\right) \mid if\ T_A \ge T_B, I_A \le I_B, F_A \le F_B\right\}$$

viii. $\mu A = \mu(T_A, I_A, F_A) = \left(\sqrt[3]{1 - (1 - T_A^3)^\mu}, I_A^\mu, F_A^\mu\right)$

ix. $A^{\mu} = (T_A, I_A, F_A)^{\mu} = \left(T_A^{\mu}, \sqrt[3]{1-(1-I_A^3)^{\mu}}, \sqrt[3]{1-(1-F_A^3)^{\mu}}\right)$

Definition 1.3.7.

Let $A_i = (T_i,\ Ii, F_i)$ be a set of Fermatean Neutrosophic Numbers (FNNs) for i = 1,2,3,…..,n, where: $T_i, Ii, and\ F_i$ represent degrees of truth-membership, indeterminacy-membership and falsity-membership.

Let $w_i \in [0,1]$ be the weight of the i^{th} element such that $\sum_{i=1}^{n} w_i = 1$. Then the **Fermatean Neutrosophic set Weighted Averaging (FNWA)** operator is given.

$$FNWA(A_1, A_2, \dots \dots . A_n) = \left(\left(\sum_{i=1}^{n} w_i T_i^3\right)^{1/3}, \left(\sum_{i=1}^{n} w_i I_i^3\right)^{1/3}, \left(\sum_{i=1}^{n} w_i F_i^3\right)^{1/3}\right)$$

1.4 OUTLINE OF THE THESIS

This thesis is structured to systematically introduce, develop, and apply a decision-making methodology for supplier selection of three-dimensional (3D) printers. The methodology is rooted in Fermatean Neutrosophic sets integrated with decision-making techniques AHP and VIKOR. Each chapter has been designed to guide the reader from conceptual foundations to practical application and analysis.

Chapter 1 provides an overview of the research, including background, objectives, and significance. It reviews existing literature on 3D printer supplier selection and fuzzy/neutrosophic decision-making models. This chapter also explains key concepts, particularly the Fermatean Neutrosophic set (FNS) which forms the foundation of the proposed methodology.

Chapter 2 This chapter presents the materials, methodological framework, and illustrative model analysis used to apply the Fermatean Neutrosophic Decision-Making Methodology in selecting suitable 3D printer suppliers. It begins by defining the decision problem and explaining the data collection process, including the identification of decision criteria, alternative suppliers, and expert evaluation.

Following this, the methodology section details the mathematical modeling and procedural steps of the Fermatean Neutrosophic Analytic Hierarchy Process (FN-AHP) and the Fermatean Neutrosophic VIKOR (FN-VIKOR) method. The final section demonstrates a real-world application of the proposed model using an Illustrative model.

Chapter 3 discusses the outcomes, and compares the proposed model. The comparison emphasizes how each method handles uncertainty, expert hesitation, and complex decision structures. While both models are effective multi-criteria decision-making (MCDM) tools, Fermatean Neutrosophic Sets offer a higher capacity for representing uncertainty due to their cube-based constraint, enabling more flexibility in expressing expert opinions. In contrast, IVPF sets rely on interval-based square-sum limitations, which are relatively less expressive. The resulting criteria weights and final supplier rankings are compared and analyzed using charts and tables. The final summary indicates that the Fermatean Neutrosophic model is more robust and suitable for real-world applications requiring flexible decision modeling, such as 3D printer supplier selection in dynamic industrial environments.

The thesis concludes the proposed Fermatean Neutrosophic decision-making model effectively addresses uncertainty and enhances the accuracy of supplier selection in 3D printers. Comparative results validate its superiority over existing fuzzy MCDM approaches, making it a robust tool for real-world applications.

CHAPTER 2

CHAPTER 2

FERMATEAN NEUTROSOPHIC SETS IN DECISION MAKING

2.1 INTRODUCTION

This chapter introduces the supplier selection problem using three-dimensional (3D) printers. 3D printers are essential for creating complex, customized parts quickly and cost-effectively, particularly in industries such as aerospace, healthcare, and manufacturing. They facilitate innovation through rapid prototyping and minimize material waste compared to traditional methods. Selecting a reliable 3D printer supplier ensures access to high-quality machines, technical support, and long-term value, ultimately maintaining consistent production quality. It highlights the application of **the Fermatean Neutrosophic-Analytic Hierarchy Process (FN-AHP)** and **VIseKriterijumska Optimizacijia I Kompromisno Resenje (VIKOR)** to address uncertainties of criterias. The integration of the Fermatean Neutrosophic set (FN-AHP and VIKOR) allows for more flexibility in expressing expert opinions.

The chapter begins by introducing the system architecture consists of supplier evaluation criteria. FNS provides a robust framework for managing uncertainty and multiple criteria. The model enables effective supplier evaluation and supplier selection, making FNDM a powerful tool for industries requiring high precision and reliability.

With the rapid advancement and widespread adoption of 3D printing technology across various industries, selecting the most suitable 3D printer supplier has become a critical strategic decision for businesses aiming to enhance productivity, customization, and innovation. However, this selection process involves multiple conflicting criteria such as Cost, Benefit, Accessibility to Technology, Logistic Support, and Technical service, often under uncertain and imprecise environments. Traditional decision-making methods fall short in handling such complex and vague evaluations provided by experts. Therefore, there is a need for a robust, flexible, and uncertainty-aware decision-making framework to evaluate and rank 3D printer suppliers effectively. This research aims to address this gap by developing a Fermatean Neutrosophic Multi-Criteria

Decision-Making (MCDM) methodology to improve the reliability and accuracy of supplier selection decisions.

In the context of 3D printer supplier selection, where expert opinions may be inconsistent, hesitant, or partially known, FNSs provide a more reliable modeling environment. In this study, the FN-AHP method is used to determine the importance weights of selection criteria, and the FN-VIKOR method is employed to rank the alternative suppliers. This integrated decision-making framework ensures a robust, comprehensive evaluation of alternatives in a highly uncertain environment. Moreover, statistical analysis and sensitivity testing have been conducted to validate the robustness of the proposed methodology.

2.2 OVERVIEW OF SUPPLIER SELECTION IOF THREE-DIMENSIONAL (3D) PRINTERS

In recent years, additive manufacturing, more commonly known as three-dimensional (3D) printing, has revolutionized the industrial landscape. From prototyping and tooling to end-use production, 3D printing is being adopted across multiple sectors including aerospace, automotive, healthcare, and consumer electronics. With the technology, the role of reliable and high-performance 3D printer suppliers becomes increasingly significant. Selecting the right 3D printer supplier is not merely a procurement activity but a strategic decision that affects production Cost (C), Benefit (B), Accessibility to technology (A), Logistics Support (L), and Technical service (T).

To address these limitations, this study proposes the use of Fermatean Neutrosophic sets with Analytic Hierarchy Process (AHP) and VIse Kriterijumska Optimizacijia I Kompromisno Resenje (VIKOR) resulting in a FN-AHP and VIKOR. FNS was selected for the supplier selection of 3D printers a more powerful and flexible framework to handle uncertainty, imprecision, and hesitation in judgments compared to traditional fuzzy and Intuitionistic approaches.

2.3 EVALUATION CRITERIA OF 3D PRINTERS SUPPLIER SELECTION

In this study, the supplier selection problem of 3D printers is studied. Three-dimensional 3D printer supplier selection decision-making using Interval-valued Pythagorean fuzzy- AHP (IVPF-AHP) integrated VIKOR was referred to as a baseline. The same set of evaluation values, criteria, and alternatives from the Interval-valued Pythagorean fuzzy- AHP (IVPF-AHP) integrated VIKOR was considered to maintain uncertainty and comparison. For this problem, the main and sub-criteria are taken and the most appropriate ones are determined by consulting with the experts. The experts are determined by considering their experiences with the supplier selection problem. The main and sub-criteria can be seen in Table 2.1.1

Table 2.3.1. Supplier selection criteria for 3D printers

Main-criteria	**Sub-criteria**
Cost (C)	
	Product price (C_1)
	Cost of the material/equipment (C_2)
	Energy consumption cost of 3D printers (C_3)
Benefit (B)	
	The compatibility of materials such as filament and nozzle (B_1)
	Customer satisfaction (B_2)
	Different type of 3D printers (B_3)
Accessibility to technology (A)	
	Geometric complexity (A_1)
	Extruders (A_2)
	Layer thickness (A_3)
	Waste disposal (A_4)
	Build speed (A_5)
Logistics support (L)	
	Delivery lead time / On-time delivery(L_1)
	Delivery liability / Perfect delivery(L_2)
Technical service (T)	

	Ease of assembly (T_1)
	Interface installation (T_2)
	Spare part (T_3)
	Easy maintenance (T_4)

The supplier selection problem of 3D printers is considered and classified five different main criteria as Cost (C), Benefit (B), Accessibility to Technology (A), Logistics Support (L), and Technical Service (T) through literature review and expert interviews.

Cost (C) is one of the main criteria for selecting the right supplier. Due to the use of new technology and their limited availability in the market, the prices of 3D printers were quite high. The widespread adoption of 3D printers and the increase in product variety have led to a decrease in selling prices. However, whether the suppliers can provide the proper service that meets the business needs should be considered, as well as the price.

The cost criterion has three sub-criteria;

- Product Price (C1),
- Cost of the material/equipment (C2) and
- Energy consumption cost of 3D printers (C3).

Benefit (B) is the second main criterion. In order for enterprises to maintain their dominance in the sector, they must produce both affordable and quality products.

Quality criterion consists of three sub-criteria;

- The compatibility of materials such as filament and nozzle (B1),
- Customer satisfaction (B2) and
- Different types of 3D printers (B3).

The compatibility of materials such as filament and nozzle (B1), Filament is one of the essential materials used in the 3D printing process. The quality and properties of the filament directly impact the quality and success of 3D printing. The nozzle directly affects the level of detail and precision in the 3D printing process. The proper selection of the nozzle is crucial for achieving high-quality prints. Customer satisfaction (B2), if the product meets customer requirements, and the customer is satisfied with the service provided, this leads to customer satisfaction. Understanding the needs and expectations of customers and planning how services can be delivered within this framework is very important. With different types of 3D printers (B3), it is very significant to find product options in different types and capacities according to the specifications of the customer to find the product that the customer desires.

The **Accessibility to Technology (A)** is the third main criterion. 2D printers perform the process of printing existing objects' letters or visuals, while 3D printers enable the physical touch of objects. In this way, 3D printers have been designed using innovative technology.

The accessibility to technology criterion consists of five sub-criteria;

- Geometric complexity (A1),
- Extruders (A2),
- Layer thickness (A3),
- Waste disposal (A4) and
- Build speed (A5).

These criteria are crucial for 3D printers to operate at the desired performance level.

Logistics Support (L) is the fourth main criterion. No matter how quality the product is or how well it is promoted, if the consumer has difficulty in finding that product, the desire for that product will decrease over time and the tendency towards alternatives will begin.

The logistics support criterion has two sub-criteria;

- Delivery lead time/on-time delivery (L1) and
- Delivery reliability/Perfect delivery (L2).

Delivery lead time/On-time delivery (L1), the delay in this period also delays the delivery to the customer. The Delivery reliability/Perfect delivery (L2) criterion is very important as it is a disadvantage for the company if the product is missing or damaged when delivering the product.

T**echnical Service (T)** is the final criterion. It is very important for after-sales service that the product is installed or assembled and running after purchase.

The technical support criterion consists of four sub-criteria;

- Ease of assembly (T1),
- Interface installation (T2),
- Spare part (T3) and
- Easy maintenance (T4).

Ease of assembly (T1) by evaluating both the conditions at the installation site and all factors with which the product can proceed more easily and quickly. The interaction between users and 3D printers produced with advanced technology will be enhanced thanks to a comprehensible interface installation (T2), causing increased user satisfaction. It is significant to be able to detect and supply the required spare parts as soon as possible. Therefore, the Spare part (T3) criterion plays an important role. There are different assembly types depending on the 3D printer models. With technological developments, devices are constantly being renewed. The precision of 3D printers produced with advanced technology necessitates careful attention to maintenance. Therefore, the importance of the technical team's knowledge in ensuring ease of maintenance (T4) is significant.

2.4 METHODS

In recent years, three-dimensional (3D) printing has emerged as a transformative technology across numerous industries, revolutionizing traditional manufacturing paradigms. Its ability to rapidly produce complex geometries, reduce material waste, and enable customization has made it indispensable in sectors such as aerospace, healthcare, automotive, electronics, and consumer goods. The demand for 3D printing is fueled by the growing need for flexible production systems, faster prototyping cycles, and cost-effective small-batch manufacturing.

As 3D printing technologies evolve, the market is flooded with a wide variety of 3D printer suppliers, each offering machines with different specifications, capabilities, and reliability standards. Choosing the right supplier becomes a strategic decision that can directly impact the Cost, Benefit, Accessibility to technology, Logistics support, and Technical service of production. Poor supplier selection may result in operational inefficiencies, substandard output, and increased maintenance or downtime. Therefore, there is an urgent need to adopt a systematic and robust decision-making framework to evaluate and select the most suitable 3D printer suppliers.

The complexity of this decision stems from the presence of multiple, often conflicting criteria such as Cost, Benefit, Accessibility to technology, Logistic support, and Technical service. Furthermore, in real-world scenarios, decision-makers frequently face uncertain, vague, or incomplete information, making traditional crisp evaluation techniques insufficient. To address this, advanced multi-criteria decision-making (MCDM) methodologies such as Interval-Valued Pythagorean Fuzzy AHP (IVPF-AHP) and Fermatean Neutrosophic AHP (FN-AHP) are utilized to handle imprecise and hesitant data more effectively.

The initial analysis was conducted using an Interval-Valued Pythagorean Fuzzy AHP (IVPF-AHP) and IVPF-VIKOR method; however, due to the presence of high indeterminacy in the expert evaluations, it was necessary to adopt a more flexible and uncertainty-tolerant approach. There are many Multi-Criteria Decision-Making (MCDM) methods, that handle uncertainty, imprecision, and hesitation in expert judgments and decision-maker preferences. Among them, the Fermatean Neutrosophic Analytic Hierarchy Process (FN-AHP) and Vise Kriterijumska Optimizacijia I Kompromisno Resenje (VIKOR) were chosen.

Therefore, the Fermatean Neutrosophic Analytic Hierarchy Process (FN-AHP) and VIse Kriterijumska Optimizacijia I Kompromisno Resenje (VIKOR) method was employed, which is specifically designed to handle situations with uncertainty, imprecision, and hesitation. This method allowed for a more realistic representation of expert input by incorporating the degrees of truth, indeterminacy, and falsity.

2.5. FERMATEAN NEUTROSOPHIC SET IN DECISION-MAKING:

Fermatean neutrosophic Analytic Hierarchy Process (AHP) combines the AHP decision-making framework with the concept of Fermatean neutrosophic sets to handle uncertainty and vagueness in evaluations and judgments.

The MCDM Fermatean Neutrosophic AHP approach is explained in the following section presents the step-by-step algorithm used to implement the Fermatean Neutrosophic AHP method for pairwise comparisons to do the ranking in Multi Criteria Decision Making.

2.5.1. THE STEPS OF FN-AHP

The steps of the FN-AHP method can be explained as follows :

STEP 1: Construct the Fermatean Neutrosophic pairwise comparison matrix $\widetilde{a_{ij}}_{(n\times n)}$ with respect to experts' opinion.

$$\widetilde{a_{ij}} = \left(T_{ij}, I_{ij}, F_{ij}\right) \text{ with } T_{ij}^3 + F_{ij}^3 \leq 2 \text{ , } I_{ij} = 2 - T_{ij}^3 - F_{ij}^3$$

STEP 2: Construct the difference matrix $d_{ik} = T_{ik}^3 - F_{ik}^3$ to measure consistency or deviations in judgments.

STEP 3: Construct the multiplicative score matrix $S = \left(s_{ij}\right)$

$$s_{ij} = \sqrt[3]{1000\,.\,d_{id}}$$

STEP 4: Calculate the determinacy value by using $\delta_{ik} = 1 - (T_{ik}^3 + F_{ik}^3)$

STEP 5: Determine Unnormalized priority weights $T = (t_{ik})$

$$t_{ik} = s_{ik}.\,t_{ik}$$

STEP 6: Find the normalized weights w_i by using

$$w_i = \frac{t_{ik}}{\sum_{k=1}^{m} t_{ik}} \quad \text{for i=1,2,3….m}$$

2.5.2. VIKOR

The Vise Kriterijumsa Optimizacija I Kompromisno Resenje (VIKOR) method was first developed by Opricovic and Tzeng for multi-criteria optimization of systems with complex structures. The VIKOR method helps to select the best alternative by using a multi-criteria ranking index to rank alternatives under a set of criteria. The VIKOR method is built from Lp-metric that measures the distance of alternative i from the ideal solutions.

$$L_i^p = \left[\sum_{j=1}^{n} w_j \left(\frac{\left|f_j^* - f_{ij}\right|}{f_j^* - f_j^-}\right)^p\right]^{1/p}$$

Where $1 \leq p \leq \infty$; i=1,2,3,……m

Within the VIKOR method, $L_i^{p=1}$ as S_i and $L_i^{p=\infty}$ as R_i are used to formulate ranking measures.

S_i is a maximum group utility "majority", and

R_i is a minimum individual regret of the "opponent".

The steps of the ranking algorithm VIKOR can be explained as follows:

Step 1. Calculate the best f_j^* and worst f_j^* values of all criterion functions j=1,2,…..,n. Assume that $the\ j^{th}$ function denotes benefits :

$$f_j^* = max_i f_{ij}$$

$$f_j^- = min_i f_{ij}$$

Step 2: Compute the values of S_i and R_i. S_i is the synthesized gap for all criteria and R_i is the maximal gap in the I criterion for prior improvement.

$$S_i = \sum_{j=1}^{n} w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_j^-}$$

$$R_i = max_j \left[w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_j^-}\right]$$

Step 3: Calculate Q_i values

$$Q_i = v\, .\, \frac{S_i - S^*}{S^- - S^*} + (1 - v)\, .\, \frac{R_i - R^*}{R^- - R^*}$$

Where $S^* = min_i S_i$, $S^- = max_i S_i$, $R^* = min_i R_i$, $R^- = max_i R_i$, and v introduce the weight for the strategy of "maximum group utility", $(1 - v)$ is the weight of the individual regret of the "opponent".

Step 4: Sort the alternatives by the values of S_i, R_i, and Q_i in descending order. Propose the alternative $A^{(1)}$ as a compromise solution which is arranged by the measure minQ_i if the two conditions are satisfied:

Condition 1: Acceptable advantage

$$Q\left(A^{(2)}\right) - Q\left(A^{(1)}\right) \leq \frac{1}{(m-1)}$$

Where m refers to the number of alternatives and $A^{(2)}$ is the second position among the alternatives ranked by Q_i.

Condition 2: Acceptable stability in decision making: Alternative $A^{(1)}$ must also be the best ranked by S_i and/or R_i.

If one of the conditions is not satisfied, then a set of compromise solutions is proposed, which consists of:

- Alternatives $A^{(1)}$ and $A^{(2)}$ if only condition 2 is not satisfied, or
- Alternatives $A^{(1)}, A^{(2)}, \dots \dots A^{(M)}$ if condition 1 is not satisfied; $A^{(M)}$ is determined by the relation $Q\left(A^{(M)}\right) - Q\left(A^{(1)}\right) < D(Q)$ for maximum M.

2.6 ILLUSTRATION

With the widespread use of 3D printers in many sectors, the number of 3D printer suppliers has increased. Businesses must find the most suitable supplier among these supplier companies. For this reason, it is of great importance for the sector to determine the criteria that should be taken into account when selecting their supplier among the enterprises supplying 3D printers to the company. The integrated FN-AHP and VIKOR methods have been used in the study.

The necessary criteria to be used in the selection of a 3D printer supplier and the criteria are determined in line with the interviews made with three expert teams with sufficient knowledge in the field. The criteria weights obtained using FN-AHP have been verified by the AHP method. Finally, the supplier scores obtained from the criterion weights of the two methods have been analyzed and their validity has been confirmed. The hierarchical structure of the application is shown in Figure 2.6.1

Criterion weights are found using the FN-AHP method. Criteria weights are transferred to the VIKOR method, and five alternative suppliers are evaluated with the VIKOR method. After that, the statistical analysis is done by Pearson Correlation Coefficient and Paired Simple tests in SPSS software.

Experts were asked to evaluate the degree of influence of the criteria on each other with fuzzy linguistic expressions shown in Table 2.6.1. The impact assessment among the criteria by one of the experts is shown in Table 2.7.1. Linguistic expressions are translated into FNs. PFNs with interval values corresponding to the linguistic evaluation of one of the experts are shown in Table 2.7.2. The consistency rates of each expert's evaluation matrix are calculated, and it is concluded that it is below 0.1. Criterion weights of the experts have been determined equally based on their years of experience in their field. Similarly, all evaluations made by the rest of the experts are translated into FNs. FNs are made into a single matrix using FNWA. The paired comparison matrix for the main criteria is shown in Table 2.7.3. The difference matrix shown in Table 2.7.4 is obtained by using the pairwise comparison matrix, $d_{ik} = T_{ik}^3 - F_{ik}^3$. The interval multiplicative matrix shown in Table 2.7.5 is obtained by using the difference matrix, $s_{ij} = \sqrt[3]{1000. d_{ij}}$. Using $\delta_{ik} = 1 - (T_{ik}^3 + F_{ik}^3)$, certainty values are shown in Table 2.7.6. An unnormalized weight matrix is derived with certainty values using $t_{ik} = s_{ik}. t_{ik}$ shown in Table 2.7.7. With the help of $w_i = \frac{t_{ik}}{\sum_{k=1}^{m} t_{ik}}$, normalized priority weights are calculated and shown in Table 2.7.8. According to the criterion weights obtained from the FN-AHP shown in Table 2.7.9, it is seen that the most important criterion to be considered in the selection of suppliers among the 3D printer brands in the sector is Quality. Supplier enterprises should focus on Quality and Technical Service criteria to increase their 3D printer sales.

Figure 2.6.1. The hierarchical structure of the application

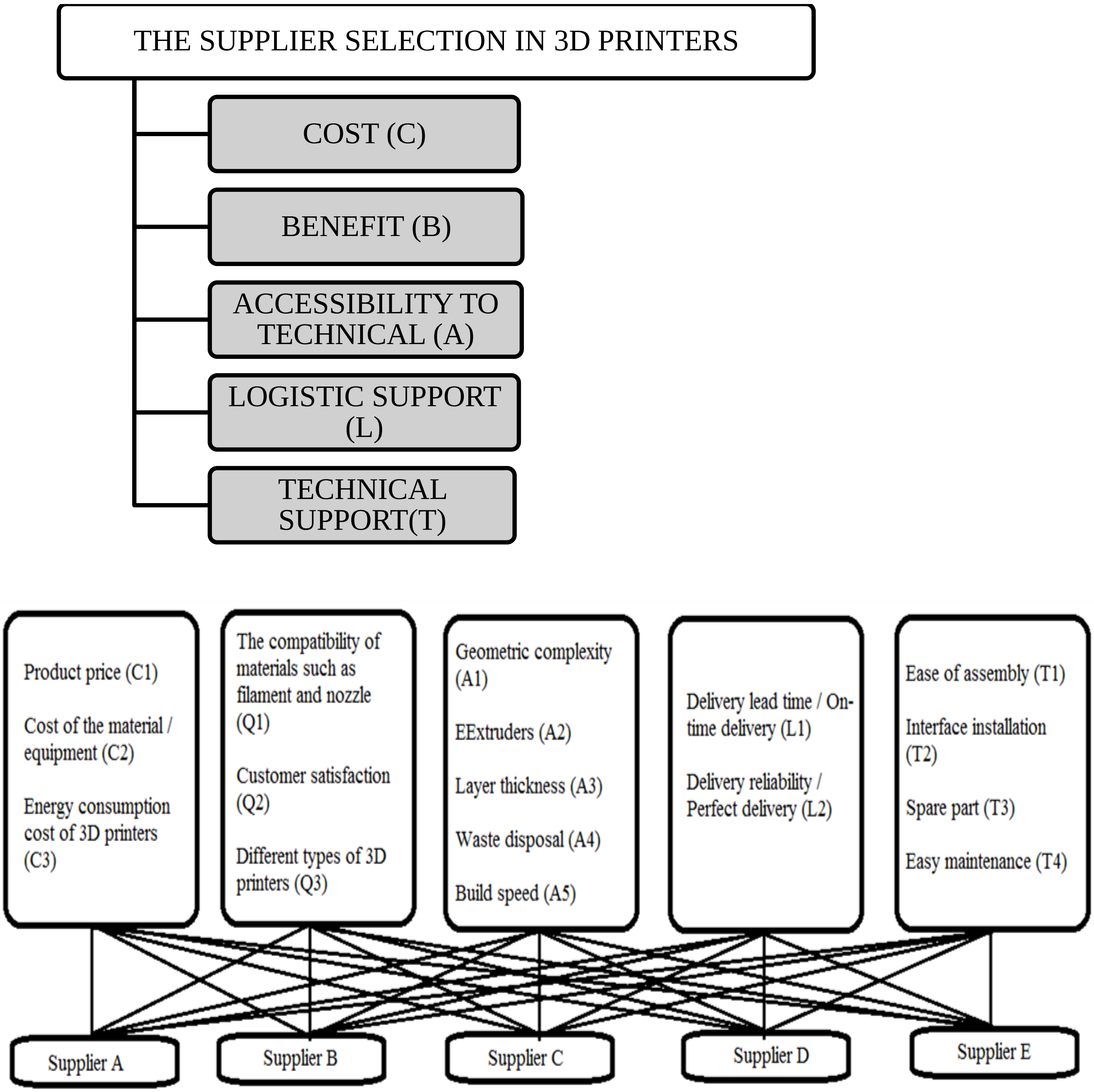


Table 2.6.1. Weighing scale for FN-AHP

Linguistic terms	(T, F, I)
Certainly Low Importance (CLI)	(0.00, 1.00, 0.000)
Very Low Importance (VLI)	(0.10, 0.90, 0.270)
Low Importance (LI)	(0.20, 0.80, 0.480)
Below Average Importance (BAI)	(0.35, 0.65, 0.682)
Average Importance (AI)	(0.45, 0.55, 0.742)
Above Average Importance (AAI)	(0.55, 0.45, 0.742)
High Importance (HI)	(0.65, 0.35, 0.682)
Very High Importance (VHI)	(0.80, 0.20, 0.480)
Certainly High Importance (CHI)	(1.00, 0.00, 0.000)
Exactly Equal(EE)	(0.1965, 0.1965, 0.984)

Table 2.6.2. The Evaluation values of one of the experts in terms of the effect between the main criteria.

	C	B	A	L	T
C	EE	LI	LI	HI	AI
B	HI	EE	EE	HI	EE
A	HI	EE	EE	AI	EE
L	LI	LI	AI	EE	LI
T	AI	EE	EE	HI	EE

Table 2.6.3. Corresponding FNs for Linguistic Evaluation

	C	B	A	L	T
C	(0.196,0.196,0.984)	(0.20,0.80,0.48)	(0.20,0.80,0.48)	(0.65,0.35,0.68)	(0.45,0.55,0.74)
B	(0.65,0.35,0.68)	(0.196,0.196,0.98)	(0.196,0.196,0.98)	(0.65,0.35,0.68)	(0.196,0.196,0.98)
A	(0.65,0.35,0.68)	(0.196,0.196,0.984)	(0.196,0.196,0.984)	(0.45,0.55,0.74)	(0.196,0.196,0.984)
L	(0.20,0.80,0.48)	(0.20,0.80,0.48)	(0.45,0.55,0.74)	(0.196,0.196,0.984)	(0.20,0.80,0.48)
T	(0.45,0.55,0.742)	(0.196,0.196,0.984)	(0.1965,0.1965,0.984)	(0.35,0.35,0.682)	(0.1965,0.1965,0.984)

STEP 1: Construct the Fermatean Neutrosophic pairwise comparison matrix $\widetilde{a_{ij}}_{(n\times n)}$ with respect to the expert's opinion.

$$\widetilde{a_{ij}} = \left(T_{ij}, I_{ij}, F_{ij}\right) \text{ with } T_{ij}^3 + F_{ij}^3 \leq 1 \text{ , } I_{ij} = 1 - T_{ij}^3 - F_{ij}^3$$

Table 2.6.4. Pairwise Comparision Matrix of Main Criteria

	C	B	A	L	T
C	(0.75,0.10,0.43)	(0.70,0.15,0.47)	(0.65,0.20,0.51)	(0.80,0.05,0.41)	(0.68,0.18,0.48)
B	(0.68,0.18,0.48)	(0.75,0.10,0.43)	(0.70,0.15,0.47)	(0.72,0.12,0.45)	(0.70,0.15,0.47)
A	(0.65,0.20,0.51)	(0.72,0.12,0.45)	(0.75,0.10,0.43)	(0.68,0.18,0.48)	(0.70,0.15,0.47)
L	(0.80,0.05,0.41)	(0.72,0.12,0.45)	(0.68,0.18,0.48)	(0.75,0.10,0.43)	(0.70,0.15,0.47)
T	(0.68,0.18,0.48)	(0.70,0.15,0.47)	(0.70,0.15,0.47)	(0.70,0.15,0.47)	(0.75,0.10,0.43)

STEP 2: Construct the difference matrix $d_{ik} = T_{ik}^3 - F_{ik}^3$ to measure consistency or deviations in judgments.

Table 2.6.5. Differences matrix of the Main Criteria

	C	B	A	L	T
C	(0.00,0.00,0.00)	(0.05,−0.05,−0.04)	(0.10,−0.10,−0.08)	(−0.05,0.05,0.02)	(0.07,−0.08,−0.05)
B	(−0.05,0.05,0.04)	(0.00,0.00,0.00)	(0.02,−0.03,−0.02)	(−0.04,0.06,0.03)	(−0.02,0.03,0.00)
A	(−0.10,0.10,0.08)	(−0.02,0.03,0.02)	(0.00,0.00,0.00)	(−0.03,0.06,0.03)	(−0.05,0.05,0.04)
L	(0.05,−0.05,−0.02)	(0.04,−0.06,−0.03)	(0.03,−0.06,−0.03)	(0.00,0.00,0.00)	(−0.02,0.05,0.02)
T	(−0.07,0.08,0.05)	(0.00,0.00,0.00)	(0.00,0.00,0.00)	(0.02,−0.05,−0.02)	(0.00,0.00,0.00)

STEP 4: Construct the multiplicative score matrix $S = (s_{ij})$

$$s_{ij} = \sqrt[3]{1000 \, . \, d_{id}}$$

Table 2.6.6. Interval multiplicative matrix of the Main Criteria

	C	B	A	L	T
C	(0.50,0.30,0.97)	(0.37,0.47,0.77)	(0.32,0.52,0.76)	(0.27,0.57,0.73)	(0.42,0.37,0.83)
B	(0.62,0.32,0.75)	(0.50,0.30,0.97)	(0.42,0.42,0.84)	(0.37,0.52,0.73)	(0.47,0.37,0.87)
A	(0.32,0.52,0.76)	(0.37,0.47,0.77)	(0.50,0.30,0.97)	(0.32,0.57,0.72)	(0.47,0.37,0.87)
L	(0.27,0.57,0.73)	(0.37,0.52,0.73)	(0.42,0.42,0.84)	(0.50,0.30,0.97)	(0.42,0.37,0.83)
T	(0.42,0.37,0.83)	(0.47,0.37,0.87)	(0.47,0.37,0.87)	(0.42,0.37,0.83)	(0.50,0.30,0.97)

STEP 4: Calculate the determinacy value by using $\delta_{ik} = 1 - (T_{ik}^3 + F_{ik}^3)$

Table 2.6.7. The determinacy values of Main Criteria

	C	B	A	L	T
C	1.00	0.83	0.79	0.76	0.84
B	0.87	1.00	0.71	0.79	0.68
A	0.85	0.89	1.00	0.83	0.77
L	0.82	0.86	0.76	1.00	0.72
T	0.91	0.73	0.81	0.78	1.00

STEP 5: Determine Unnormalized priority weights $T = (t_{ik})$

$$t_{ik} = s_{ik}.t_{ik}$$

Table 2.6.8. The unnormalized weights of the Main Criteria.

	C	B	A	L	T
C	0.32	0.06	0.12	0.28	0.08
B	0.91	0.32	0.67	0.95	0.14
A	0.14	0.05	0.34	0.22	0.06
L	0.11	0.07	0.16	0.34	0.05
T	0.80	0.15	0.42	0.78	0.30

STEP 6: Find the normalized weights w_i by using

$$w_i = \frac{t_{ik}}{\sum_{k=1}^{m} t_{ik}} \quad \text{for i=1,2,3....m}$$

Table 2.6.9. The normalized weights of each Criterion.

Main Criteria	w(%)
Cost	10.12
Benefit	38.76
Accessibility to technology	09.89
Logistics Support	08.67
Technical service	32.56

STEP 7: Construct the Fermatean Neutrosophic pairwise comparison matrix $\widetilde{a_{ij}}_{(n\times n)}$ with respect to the expert's opinion.

$$\widetilde{a_{ij}} = \left(T_{ij}, I_{ij}, F_{ij}\right) \text{ with } T_{ij}^3 + F_{ij}^3 \leq 1 \text{ , } I_{ij} = 1 - T_{ij}^3 - F_{ij}^3$$

weights w_i by using

$$w_i = \frac{t_{ik}}{\sum_{k=1}^{m} t_{ik}} \quad \text{for i=1,2,3....m}$$

Table 2.6.10. The pairwise comparison matrix of all the expert evaluations, and the sub-criteria weights of cost criterion.

	C_1	C_2	C_3	W(%)
C_1	(0.80,0.10,0.10)	(0.55,0.30,0.15)	(0.60,0.25,0.15)	24.60
C_2	(0.70,0.20,0.10)	(0.85,0.05,0.10)	(0.78,0.10,0.12)	57.20
C_3	(0.58,0.25,0.17)	(0.72,0.15,0.13)	(0.80,0.10,0.10)	18.20

STEP 8: Construct the Fermatean Neutrosophic pairwise comparison matrix $\widetilde{a_{ij}}_{(n\times n)}$ with respect to experts' opinions.

$\widetilde{a_{ij}} = \left(T_{ij}, I_{ij}, F_{ij}\right)$ with $T_{ij}^3 + F_{ij}^3 \leq 1$, $I_{ij} = 1 - T_{ij}^3 - F_{ij}^3$

weights w_i by using

$$w_i = \frac{t_{ik}}{\sum_{k=1}^{m} t_{ik}} \quad \text{for i=1,2,3....m}$$

Table 2.6.11. The pairwise comparison matrix of all the expert evaluations, and the sub-criteria weights of quality criterion.

	B_1	B_2	B_3	W(%)
B_1	(0.80,0.10,0.10)	(0.65,0.20,0.15)	(0.68,0.20,0.12)	52.00
B_2	(0.60,0.25,0.15)	(0.83,0.10,0.07)	(0.72,0.15,0.13)	25.90
B_3	(0.62,0.18,0.20)	(0.70,0.20,0.10)	(0.82,0.08,0.10)	22.10

STEP 9: Construct the Fermatean Neutrosophic pairwise comparison matrix $\widetilde{a_{ij}}_{(n\times n)}$ with respect to experts opinions.

$\widetilde{a_{ij}} = \left(T_{ij}, I_{ij}, F_{ij}\right)$ with $T_{ij}^3 + F_{ij}^3 \leq 1$, $I_{ij} = 1 - T_{ij}^3 - F_{ij}^3$

weights w_i by using

$$w_i = \frac{t_{ik}}{\sum_{k=1}^{m} t_{ik}} \quad \text{for i=1,2,3....m}$$

Table 2.6.12. The pairwise comparison matrix of all the expert evaluations, and the sub-criteria weights of accessibility to technology criterion.

	A_1	A_2	A_3	A_4	A_5	W(%)
A_1	(0.75,0.15,0.10)	(0.60,0.25,0.15)	(0.70,0.20,0.10)	(0.66,0.20,0.14)	(0.50,0.30,0.20)	11.10
A_2	(0.68,0.20,0.12)	(0.80,0.10,0.10)	(0.77,0.13,0.10)	(0.65,0.25,0.10)	(0.70,0.20,0.10)	16.30
A_3	(0.76,0.15,0.09)	(0.68,0.22,0.10)	(0.83,0.10,0.07)	(0.64,0.25,0.11)	(0.78,0.10,0.12)	23.30
A_4	(0.65,0.20,0.15)	(0.58,0.30,0.12)	(0.66,0.25,0.09)	(0.81,0.10,0.09)	(0.74,0.15,0.11)	18.90
A_5	(0.70,0.15,0.15)	(0.65,0.25,0.10)	(0.80,0.10,0.10)	(0.77,0.13,0.10)	(0.85,0.05,0.10)	30.40

STEP 10: Construct the Fermatean Neutrosophic pairwise comparison matrix $\widetilde{a_{ij}}_{(n\times n)}$ with respect to experts opinions.

$$\widetilde{a_{ij}} = \left(T_{ij}, I_{ij}, F_{ij}\right) \text{ with } T_{ij}^3 + F_{ij}^3 \leq 1 \text{ , } I_{ij} = 1 - T_{ij}^3 - F_{ij}^3$$

weights w_i by using

$$w_i = \frac{t_{ik}}{\sum_{k=1}^{m} t_{ik}} \quad \text{for i=1,2,3….m}$$

Table 2.6.13. The pairwise comparison matrix of all the expert evaluations and the sub-criteria weights of the logistic support criterion.

	L_1	L_2	W(%)
L_1	(0.80,0.10,0.10)	(0.60,0.25,0.19)	19.50
L_2	(0.72,0.15,0.13)	(0.85,0.05,0.10)	80.50

STEP 11: Construct the Fermatean Neutrosophic pairwise comparison matrix $\widetilde{a_{ij}}_{(n\times n)}$ with respect to experts opinions.

$$\widetilde{a_{ij}} = (T_{ij}, I_{ij}, F_{ij}) \text{ with } T_{ij}^3 + F_{ij}^3 \leq 1 \text{ , } I_{ij} = 1 - T_{ij}^3 - F_{ij}^3$$

weights w_i by using

$$w_i = \frac{t_{ik}}{\sum_{k=1}^{m} t_{ik}} \quad \text{for i=1,2,3....m}$$

Table 2.6.14. The pairwise comparison matrix of all the expert evaluations, and the sub-criteria weights of the technical service criterion.

	T_1	T_2	T_3	T_4	W(%)
T_1	(0.80,0.10,0.10)	(0.66, 0.20,, 0.14)	(0.72, 0.20, 0.08)	(0.70, 0.15, 0.15)	20.80
T_2	(0.70,0.20,0.10)	(0.85,0.05,0.10)	(0.74, 0.15, 0.11)	(0.82,0.10,0.08)	25.20
T_3	(0.62,0.25,0.13)	(0.78,0.10,0.12)	(0.80, 0.10, 0.10)	(0.73,0.15,0.12)	19.10
T_4	(0.65,0.20,0.15)	(0.72,0.15,0.13)	(0.76, 0.13, 0.11)	(0.85,0.05,0.10)	34.90

STEP 12: $L_i^p = \left[\sum_{j=1}^{n} w_j \left(\frac{|f_j^* - f_{ij}|}{f_j^* - f_j^-}\right)^p\right]^{1/p}$

Where $1 \leq p \leq \infty$; i=1,2,3,......m

Calculate the best f_j^* and worst f_j^* values of all criterion functions j=1,2,.....,n. Assume that the j^{th} function denotes benefits :

$$f_j^* = max_i f_{ij}$$

$$f_j^- = min_i f_{ij}$$

Table 2.6.15. Evaluation scores of 3D printer suppliers belonging to different brands according to the criteria

	A	B	C	D	E	f_j^*	f_j^-
C1	24	26	29	61	58	61	24
C2	38	26	47	39	61	61	25
C3	77	26	29	25	81	81	25
B1	72	26	20	31	76	76	20
B2	61	26	44	28	71	71	28
B3	76	26	14	35	78	78	14
A1	50	26	22	41	71	71	22
A2	58	26	41	43	81	81	26
A3	72	26	38	51	89	89	28
A4	59	26	30	29	76	76	29
A5	78	26	45	33	94	94	33
L1	54	26	50	43	67	67	13
L2	72	26	45	64	78	78	33
T1	77	26	41	51	82	82	33
T2	69	26	38	53	75	75	38
T3	73	26	43	61	85	85	29
T4	80	26	52	67	91	91	36

STEP 13: Compute the values of $S_i$and R_i. S_i is the synthesized gap for all criteria and R_i is the maximal gap in the I criterion for prior improvement.

$$S_i = \sum_{j=1}^{n} w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_j^-}$$

$$R_i = max_j \left[w_j \cdot \frac{f_j^* - f_{ij}}{f_j^* - f_j^-} \right]$$

Calculate Q_i values

$$Q_i = v \cdot \frac{S_i - S^*}{S^- - S^*} + (1 - v) \cdot \frac{R_i - R^*}{R^- - R^*}$$

Table 2.6.16. Ranking of 3D printer suppliers belonging to different brands according to the criteria weights obtained from the FN-AHP.

S_i	Rank	R_i	Rank	Q_i	Rank	Final Rank
0.655	A	0.090	A	0.585	A	2
0.070	B	0.042	B	0.000	B	1
0.730	C	0.179	C	0.880	C	4
0.782	D	0.184	D	0.940	D	3
0.820	E	0.190	E	0.972	E	5

When examined in terms of supplier selection in additive manufacturing, it is observed that especially cost and accessibility to Technology criteria come well after Quality and Technical service criteria.

For this reason, these two criteria are among the determining factors in supplier selection. The steps applied in the FN-AHP method for the main criteria are also applied for the sub-criteria, and the significance weights of the sub-criteria are shown in tables.

The criteria weights used in the VIKOR method come from the FN-AHP method, as the methods are used in an integrated manner. In the FN-AHP method, experts are asked to evaluate the criteria according to their importance with the fuzzy linguistic expressions shown in Table 3. For this reason, the criteria weights used in VIKOR are fuzzy. No deterministic action has been taken in criterion weights.

Experts are asked to score between 0-100 when comparing suppliers, as it would be much more difficult to compare five different 3D printer suppliers, which we define as A, B, C, D, and E, according to each criterion with linguistic expressions. For this reason, the VIKOR method has been preferred. The scores and the maximum and minimum scores of each criterion are shown in Table 2.6.15 where 0 is very bad and 100 is very good. The results obtained by calculating the group benefit average and maximum regret average of each supplier are listed in Table 2.6.16

By examining condition 1 (acceptable advantage) and condition 2 (an acceptable advantage in decision making) in the VIKOR method, according to condition 1 and condition 2, among the listed supplier's Q_i, supplier A with the smallest value has been chosen due to its highest performance level.

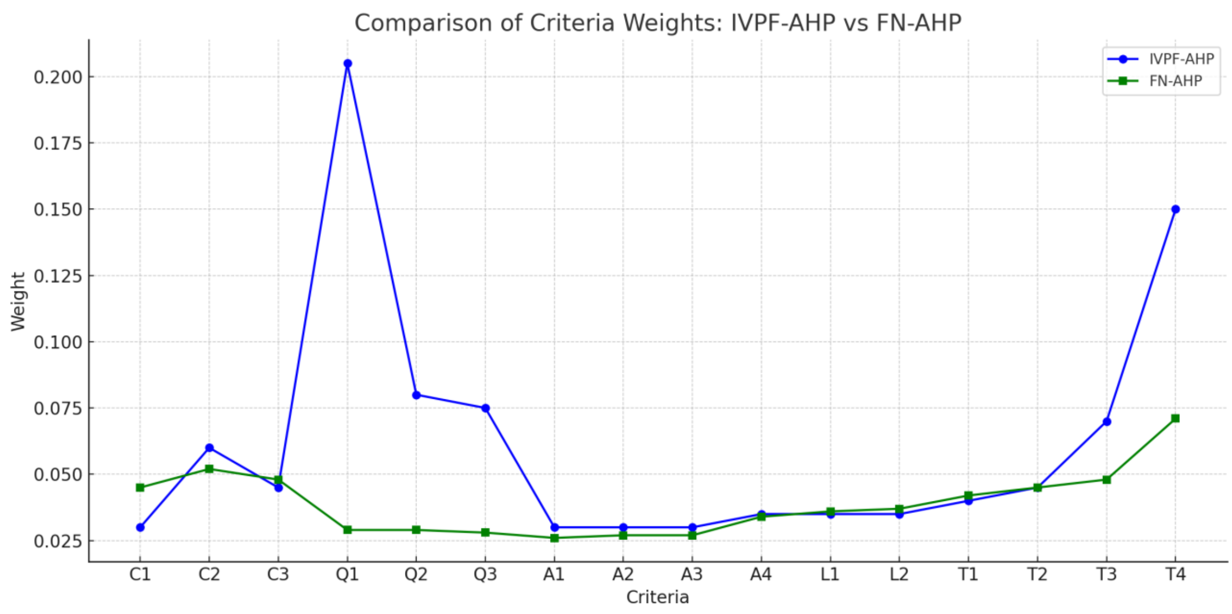
CHAPTER 3

CHAPTER 3
COMPARATIVE ANALYSIS

3.1 COMPARATIVE ANALYSIS

A chapter related to Three-Dimensional 3D printer supplier selection decision-making using Interval-valued Pythagorean fuzzy- AHP (IVPF-AHP) integrated VIKOR was referred to as a baseline. The same set of evaluation values, criteria, and alternatives from the Interval-valued Pythagorean fuzzy- AHP (IVPF-AHP) integrated VIKOR was considered to maintain uncertainty and comparison. However, instead of applying the Interval-valued Pythagorean fuzzy- AHP (IVPF-AHP) integrated VIKOR, this study utilized Fermatean Neutrosophic Sets to represent the data. The motivation behind this shift lies in the Fermatean model's enhanced ability to express higher degrees of indeterminacy, which is often encountered in Three-Dimensional 3D printer supplier selection decision-making due to limited data and expert hesitation.

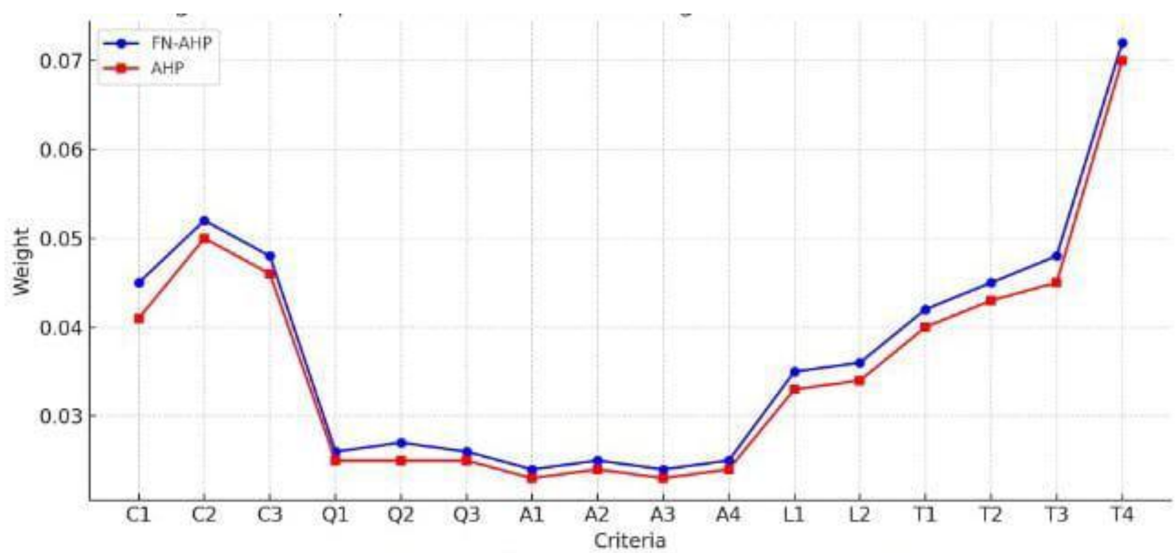
The comparison between the two methods is illustrated in the graph below, where the blue line represents the rankings obtained using the Interval-valued Pythagorean fuzzy- AHP (IVPF-AHP) approach and the Green line shows the rankings from the Fermatean Neutrosophic- AHP (FN-AHP) approach.



. The FN-AHP is more successful than the AHP method due to its flexibility in defining decision-makers and its success in modeling uncertainty in real-life problems. The correlation coefficient or r coefficient is a statistical tool used to measure the degree or strength of the relationship between two different variables. The correlation coefficient is considered to represent ≤ 0.35 weak correlations, 0.36 to 0.67 modest correlations, 0.68 to 1.00 high correlations, and ≥ 0.90 very high correlations.

The comparison between the two methods is illustrated in the graph below, where the blue line represents the rankings obtained using the Fermatean Neutrosophic- AHP (FN-AHP) approach, and the Red line shows the rankings from the AHP (AHP) approach.

Figure 3.1.1. Comparison of the criteria weights obtained from the methods



According to Figure 3.1.2, the correlation coefficient and test significance value of the methods are 0.9302 and 0.000, respectively. A very strong statistically positive correlation has been found between the criteria weights obtained from FN-AHP and the criteria weights obtained from AHP ($P < 001$). The five supplier scores are analyzed by paired sample t-test. According to Table 3.1.2 and Table 3.1.3, the 99% confidence level, test statistic and significance values are 1.735 and 0.156, respectively. The correlation coefficient according to the total scores of 3D printer suppliers with FN-AHP and AHP methods is 0.998.

Figure 3.1.2. Correlation graph of the criteria weights obtained from the methods.

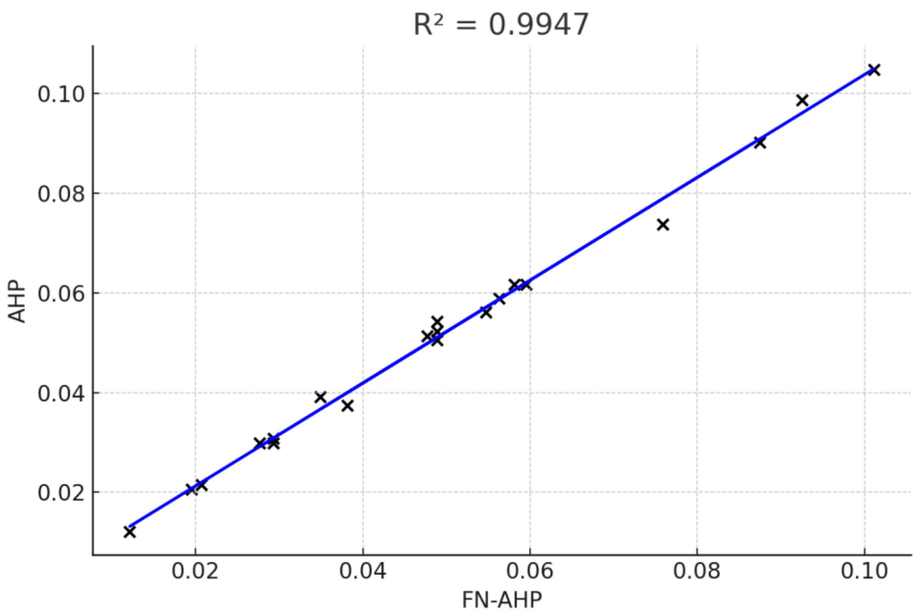


Table 3.1.1. Total scores of 3D printer suppliers according to the FN-AHP and the AHP methods.

	Criteria	A	B	C	D	E
	C	03	04	06	05	03
	B	30	20	09	12	11
FN-AHP	A	07	06	04	03	02
	L	06	06	05	06	04
	T	25	14	13	11	10
	Total	73	50	37	37	30

	Criteria	A	B	C	D	E
	C	03	02	04	04	03

AHP	B	30	18	08	10	10
	A	05	06	03	02	02
	L	05	05	04	05	03
	T	23	12	11	10	11
	Total	66	43	30	31	29

Table 3.1.2. Analysis of the criteria weights of FN-AHP and AHP methods with paired sample t-tests in five suppliers.

Paired Differences							
FN-AHP and AHP	Mean	Std Deviation	Std Error Mean	99% Confidence Interval of the Difference	T	df	Sig.(2-tailed)
	0.46000	0.59322	0.26528	-0.19683, 1.11683	1.735	4	0.156

Table 3.1.3. Correlation coefficient according to the total scores of 3D printer suppliers.

	Correlation Coefficient	Sig.
FN-AHP and AHP	0.998	0.000

A paper related to Three-Dimensional 3D printer supplier selection decision-making using Interval-valued Pythagorean fuzzy- AHP (IVPF-AHP) integrated VIKOR was referred to as a baseline. The same set of evaluation values, criteria, and alternatives from the Interval-valued Pythagorean fuzzy- AHP (IVPF-AHP) integrated VIKOR.

Table 3.1.4. Analysis of the criteria weights of IVPF-AHP and AHP methods with paired sample t-tests in five suppliers.

Paired Differences							
IVPF-AHP and AHP	Mean	Std Deviation	Std Error Mean	99% Confidence Interval of the Difference	T	df	Sig.(2-tailed)
	0.40000	0.54772	0.24495	-0.28009, 1.08009	1.633	4	0.178

Table 3.1.5. Correlation coefficient according to the total scores of 3D printer suppliers.

	Correlation Coefficient	Sig.
IVPF-AHP and AHP	1.000	0.000

The application of the Fermatean Neutrosophic Decision-Making methodology, integrating FN-AHP and FN-VIKOR, for selecting three-dimensional (3D) printer suppliers produced total scores and rankings for the evaluated suppliers, with Supplier B consistently ranked as the top choice. The correlation coefficient between the criteria weights derived from FN-AHP and traditional AHP was 0.998, indicating a very strong positive relationship. Furthermore, a paired sample t-test on the supplier scores resulted in a p-value of 0.156, showing no statistically significant difference between the two methods at the 99% confidence level, confirming the robustness of the FN-AHP integrated model. Despite the similar rankings, the FN-AHP approach offers superior decision-making capabilities under uncertainty. Its advanced structure, based on the cubic constraint $T^3 + I^3 + F^3 \leq 1$, provides greater flexibility in modeling expert judgment involving hesitancy, vagueness, and incomplete information. Additionally, the **FN-AHP** model placed higher weights on criteria such as **Benefits and Technical Service**s, reflecting a more refined and realistic representation of industry priorities. In contrast, the IVPF-AHP method, while effective, operates within a more restricted evaluative space and may not fully capture the depth of uncertainty in expert assessments. Therefore, the Fermatean Neutrosophic methodology demonstrates superior applicability in supplier evaluation, making it a more effective tool for strategic procurement decisions under uncertainty.

SUMMARY AND CONCLUSION

This study introduces a Fermatean Neutrosophic Decision-Making methodology to address the complex problem of 3D printer supplier selection. By combining FN-AHP and FN-VIKOR, the approach effectively evaluates multiple conflicting criteria under uncertainty, including Cost, Benefit, Accessibility to Technology, Logistics Support, and Technical Service. Expert judgments were translated into Fermatean Neutrosophic Numbers, allowing a more comprehensive representation of subjective and imprecise evaluations. The results show that Benefits and Technical Service are the most influential criteria when selecting a 3D printer supplier. The proposed methodology successfully identifies the most suitable supplier from a set of alternatives, offering a structured, consistent, and reliable decision-making framework.

The comparison between the two approaches reveals significant differences in the final rankings of the alternatives. In the existing paper, **Supplier A1** was ranked highest, whereas, in the Fermatean Neutrosophic AHP and VIKOR approach applied in this study, **Supplier A2** was the top-ranked alternative. This change highlights the influence of incorporating a higher degree of indeterminacy in the decision-making process. Fermatean Neutrosophic Sets provide a more flexible and realistic representation of expert judgment.

The Fermatean Neutrosophic approach enhances the accuracy of supplier selection by addressing ambiguity and hesitation in expert input. It is a robust and practical tool for organizations aiming to select the best 3D printer supplier in a dynamic and competitive market.

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