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TRIANGULAR INTUITIONISTIC FUZZY (TIF) TOPSIS AND STATISTICAL APPROACH FOR CONVENIENCE STORE PREFERENCE RANKING

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ABSTRACT

Convenience store selection often involves subjective judgement and uncertainty, making fuzzy decision-making approaches highly suitable. This study employs the Triangular Intuitionistic Fuzzy TOPSIS (TIF-TOPSIS) method, which integrates membership and non-membership functions to better capture uncertainty in consumer preferences. Five convenience stores anonymised as Store A, Store B, Store C, Store D, and Store E, were assessed based on four benefit criteria (cleanliness, store image, product assortment and service quality) and one cost criterion (price). Data was collected from undergraduate students enrolled in a mathematics degree programme at a public higher-learning institution in the Klang Valley. The TIF-TOPSIS procedure was implemented in two phases: (i) Conversion of linguistic evaluations into triangular intuitionistic fuzzy numbers, followed by aggregation, normalisation, and weighting; and (ii) computation of the Intuitionistic Fuzzy Positive Ideal Solution (IFPIS), Intuitionistic Fuzzy Negative Ideal Solution (IFNIS), and the closeness coefficient for ranking alternatives. Results indicate that Store C is the most preferred option, followed by Store B, Store D, Store A, and Store E. Cleanliness and service quality emerged as the most important criteria, while price was identified as the key cost factor. The fuzzy findings were supported by statistical analysis, which produced results that were both consistent with the ranking patterns and of acceptable reliability. The integration of TIF-TOPSIS with statistical validation enhances decision reliability and provides a comprehensive assessment framework for convenience store selection.

2020 Mathematics Subject Classification:

Introduction

Convenience stores have become an essential part of modern retail due to their accessibility, extended operating hours, and ability to meet immediate consumer needs. In Malaysia, the rapid expansion of convenience store chains has increased competition and influenced consumer purchasing behaviour. In urban environments, where speed and convenience are often prioritised, convenience stores have become increasingly relevant [1, 2]. In this study, five convenience store chains are examined and represented using pseudonyms, namely Store A, Store B, Store C, Store D, and Store E to preserve commercial confidentiality. The evaluation of these stores is typically based on factors such as service quality, cleanliness, store image, product assortment, and price. These factors are typically assessed subjectively, which introduces a degree of uncertainty into the decision-making process [3, 4]. As a result, the selection of a preferred convenience store can be viewed as a multi-criteria decision-making problem in an uncertain environment.

Multi-criteria Decision-making (MCDM) methods are commonly used in situations where decisions need to be made across several criteria that may not always align [5]. Among the available approaches, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) has gained considerable attention due to its relatively simple structure and its effectiveness in ranking alternatives based on their closeness to the ideal and non-ideal solutions [6, 7].

The traditional TOPSIS approach is useful, but it assumes that the input data are accurate, which is frequently not the case in actual decision-making situations. In practice, evaluations are commonly expressed in vague or linguistic terms, reflecting the subjective nature of human judgement. To accommodate this, fuzzy set theory introduced by Zadeh [8] provides a useful framework for handling imprecision by allowing such evaluations to be represented more flexibly, which later led to the development of the Fuzzy TOPSIS method [9].

Even with these extensions, conventional fuzzy approaches tend to emphasise membership values and as a result it may still fall short in fully capturing the uncertainty inherent in human judgement [10, 11]. Considering both membership and non-membership information allows uncertainty to be represented more clearly. In this regard, intuitionistic fuzzy sets extend fuzzy theory by incorporating both membership and non-membership information [12]. The Triangular Intuitionistic Fuzzy TOPSIS (TIF-TOPSIS) approach has been used in a variety of decision-making situations based on this framework. Previous studies have demonstrated the usefulness of this approach in various contexts, including supplier selection, logistics evaluation, and service assessment [13, 14, 15]. In addition, more recent work has also highlighted the value of combining fuzzy decision-making techniques with statistical analysis to enhance the reliability of results [1]. These developments indicate that fuzzy-based approaches are capable of handling uncertainty in complex decision environments.

Even with these advancements, there are two problems still not fully resolved. The first concerns the limited use of intuitionistic fuzzy techniques in consumer-based decision-making, especially in retail environments. Consumer assessments are often subjective and can differ greatly amongst people, in contrast to organised decision environments. Second, while the data being obtained from uncertain and perception-based inputs, fuzzy decision-making conclusions are frequently presented as definite rankings. The results may be perceived as deterministic outcomes in the absence of other evidence, such as statistical analysis, which could lessen their credibility.

This study addresses these issues by examining consumer preferences among selected convenience stores in Malaysia using the Triangular Intuitionistic Fuzzy TOPSIS method in combination with statistical analysis. The role of statistical analysis in this study is not to validate the mathematical model, but to assess the consistency of respondents' evaluations and to support the interpretation of the resulting rankings. As a result, this study offers a better organised foundation for comprehending the results of decisions made using subjective inputs. The evaluation involves five convenience stores which are Store A, Store B, Store C, Store D, and Store E, and considers selected benefit and cost criteria, with additional support from reliability testing and expectation–performance gap analysis.

Methodology

This section outlines the procedures used to evaluate consumer preferences among five convenience stores using the TIF-TOPSIS method. The methodology consists of three main components:

i. Preliminaries on intuitionistic fuzzy sets and Triangular Intuitionistic Fuzzy Numbers (TIFNs).
ii. Data collection and criteria specification
iii. The eight computational steps of TIF-TOPSIS.

Preliminaries

This subsection introduces the fundamental mathematical concepts that underpin the TIF-TOPSIS method.

Definition 1: [12]

Let X be a universal set. An intuitionistic fuzzy set A in the universe X can be defined as $A = \{ x, \mu_A(x), v_A(x): x \in X\}$, where $\mu_A: X \to [0, 1]$ and $v_A: X \to [0, 1]$ denote the membership and non-membership degrees of the element $x \in X$, respectively.

For all $x \in X: 0 \leq \mu_A(x) + v_A(x) \leq 1$ and if $\pi_A(x) = 1 - \mu_A(x) - v_A(x)$, then $\pi_A(x)$ is the hesitancy degree of the element $x \in X$ to the set A and $\pi_A(x) \in [0, 1]$, for all $x \in X$.

Definition 2: [15]

A triangular intuitionistic fuzzy number (TIFN) can be expressed as:

$$\tilde{A}\sim = (a_1, a_2, a_3; b_1, a_2, b_3)$$

where (a_1, a_2, a_3) represents the triangular membership function and (b_1, a_2, b_3) represents the triangular non-membership function, subject to the condition $0 \leq \mu_A(x) + v_A(x) \leq 1$.

Definition 3: [16]

Let

$$\tilde{A} = (a_1, a_2, a_3; b_1, a_2, b_3) \text{ and } \widetilde{B} = (c_1, c_2, c_3; d_1, c_2, d_3)$$

be two triangular intuitionistic fuzzy numbers. The basic arithmetic operations used in this study are defined as follows:

Addition

$$\tilde{A} \oplus \tilde{B} = (a_1 + c_{11}, a_2 + c_2, a_3 + c_3;\ b_{11} + d_{11}, a_2 + c_2, b_3 + d_3)$$

Scalar Multiplication

For a positive scalar $\lambda > 0$,

$$\lambda\tilde{A} = (\lambda a_1, \lambda a_2, \lambda a_3; \lambda b_1, \lambda a_2, \lambda b_3)$$

Definition 4: [17]

Let $A_1 = (\phi_{11}, \phi_{12}, \phi_{13}; \psi_{11,}\psi_{12,}\psi_{13})$ and $A_2 = (\phi_{21}, \phi_{22}, \phi_{23}; \psi_{21,}\psi_{22,}\psi_{23})$ be two Triangular Intuitionistic Fuzzy Numbers (TIFNs). The Euclidean-based vertex distance is defined as the distance between TIFNs as follows:

$$d(A_1, A_2) = \sqrt{\frac{(\phi_{11}-\phi_{21})^2+(\phi_{12}-\phi_{22})^2+(\phi_{13}-\phi_{23})^2+(\psi_{11}-\psi_{21})^2+(\psi_{12}-\psi_{22})^2+(\psi_{13}-\psi_{23})^2}{6}}$$

(2.1)

Data Collection

Five prominent convenience store chains operating in the Klang Valley were selected as the alternatives for this study. In order to comply with commercial confidentiality requirements, the real names of these establishments have been anonymised and are designated as Store A through Store E. The selected alternatives represent a mix of well-known brands representing domestic, international, and premium-tier convenience retail models. Store A is a well-established 24-hour international franchise with the largest and most widespread network of outlets in the country. Store B is a highly popular Asian-origin chain that disrupted the local market by heavily emphasising high-quality, ready-to-eat meals, fresh food counters, and a premium store image.

Meanwhile, Store C is a trend-forward international brand known for its modern lifestyle aesthetic. Next, Store D is an outlet with a distinctive product line that includes specialty street food options, imported trendy snacks, and a cozy, cafe-like retail setting. Store D is another prominent chain East Asian-origin that competes in the premium convenience space. It places a strong focus on a wide assortment of imported cultural food items, fresh bakery goods, and targeted consumer promotions. Lastly, Store E is a dominant, homegrown Malaysian 24-hour retail chain. Unlike the premium international brands, this store is widely recognised for its highly competitive pricing, affordability, and a highly practical assortment of daily household groceries and necessities.

The data was collected between March and April 2024 via a structured questionnaire administered to 70 undergraduate students enrolled in a mathematics degree programme at a public university in the Klang Valley. Respondents evaluated five convenience stores using linguistic terms converted into TIFNs. Four criteria were selected as benefit criteria which are cleanliness, store image, product assortment, and service quality, while price was used as the cost criterion. The hierarchical decision structure used in this study is depicted in Figure 1.

Triangular Intuitionistic Fuzzy TOPSIS (TIF-TOPSIS)

The TIF-TOPSIS method is applied through a sequence of eight steps, as outlined in the following section. Table 1 presents the triangular intuitionistic fuzzy numbers (TIFNs) assigned to the criteria weights, while Table 2 provides the corresponding TIFNs for the sub-criteria alternatives [17].

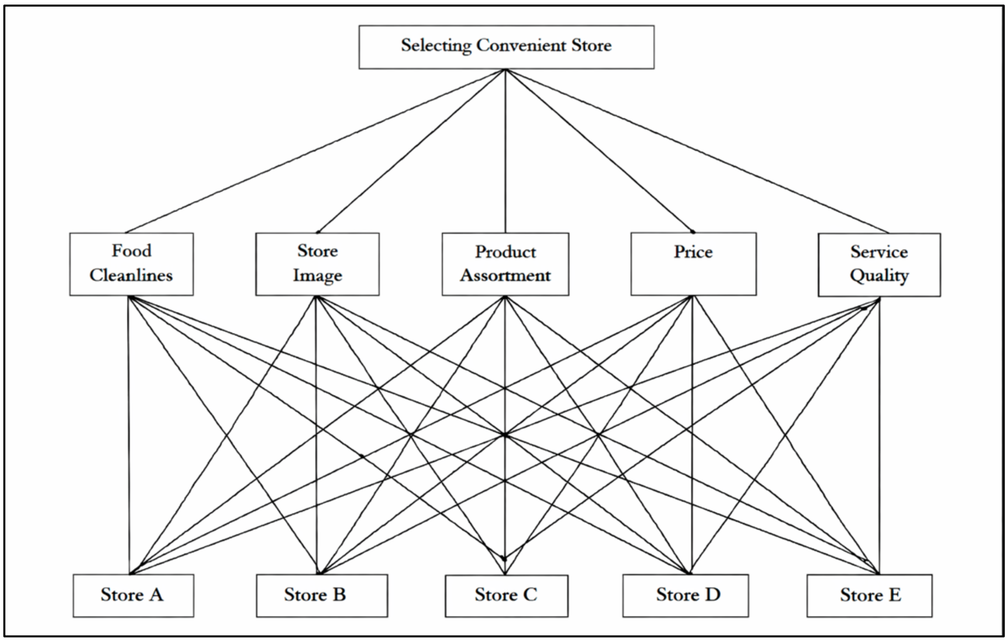

Figure 1: The decision hierarchical structure

Table 1: Triangular Intuitionistic Fuzzy Numbers (TIFNs) for criteria weights

Linguistic Term	Symbol	Triangular Intuitionistic Fuzzy Numbers (TIFNs)
Very low	VL	(0, 0, 0.1; 0, 0, 0.2)
Low	L	(0, 0.1, 0.3; 0, 0.1, 0.4)
Medium low	ML	(0.1, 0.3, 0.5; 0.05, 0.3, 0.55)
Medium	M	(0.3, 0.5, 0.7; 0.2, 0.5, 0.8)
Medium high	MH	(0.5, 0.7, 0.9; 0.45, 0.7, 0.95)
High	H	(0.7, 0.9, 1; 0.6, 0.9, 1)
Very high	VH	(0.9, 1, 1; 0.8, 1, 1)

Table 2: Triangular Intuitionistic Fuzzy Numbers (TIFNs) for sub-criteria alternatives

Linguistic Term	Symbol	Triangular Intuitionistic Fuzzy Numbers
Very poor	VP	(0, 0, 1; 0, 0, 2)
Poor	P	(0, 1, 3; 0, 1, 4)
Medium poor	MP	(1, 3, 5; 0.5, 3, 5.5)
Medium	M	(3, 5, 7; 2, 5, 8)
Medium good	MG	(5, 7, 9; 4.5, 7, 9.5)
Good	G	(7, 9, 10; 6, 9, 10)
Very good	VG	(9, 10, 10; 8, 10, 10)

Step 1

Aggregate the decision makers' opinions. If there are d decision-makers, the aggregated weight of criterion C_j and the aggregated rating of alternative A_i with respect to criterion C_j are obtained by averaging the corresponding TIFNs as follows:

$$\breve{a}_j = \frac{1}{d}\left(\breve{a}_j^1 \oplus \breve{a}_j^2 \oplus \cdots \oplus \breve{a}_j^d\right) \tag{2.2}$$

$$\breve{e}_{ij} = \frac{1}{d}\left(\breve{e}_{ij}^1 \oplus \breve{e}_{ij}^2 \oplus \cdots \oplus \breve{e}_{ij}^d\right) \tag{2.3}$$

where $\breve{a}_j^k$ denotes the TIFN weight assigned by decision-maker k to criterion C_j, $\breve{e}_{ij}^k$ denotes the TIFN rating assigned by decision-maker k to alternative A_i under criterion C_j, and d is the total number of decision-makers.

Step 2

Create the IF decision matrix after evaluating the aggregated ratings of alternatives and the aggregated criteria. The decision-making matrix has the following expression once the criteria's weights and group ratings of the options have been determined.

$$\breve{E} = \begin{bmatrix} \breve{e}_{11} & \breve{e}_{12} & \cdots & \breve{e}_{1j} \\ \breve{e}_{21} & \breve{e}_{22} & \cdots & \breve{e}_{2j} \\ \vdots & \vdots & \ddots & \vdots \\ \breve{e}_{i1} & \breve{e}_{i2} & \cdots & \breve{e}_{ij} \end{bmatrix} \tag{2.4}$$

$$\breve{A} = \{\breve{a}_1, \breve{a}_2, \ldots, \breve{a}_j\} \tag{2.5}$$

Where $\breve{e}_{ij}$ (for all *i,j*) and $\breve{a}_j$ (for all *j*) are in the form of linguistic variables and it is represented as:

$$\breve{e}_{ij} = ({\alpha^{(1)}}_{ij}, {\alpha^{(2)}}_{ij}, {\alpha^{(3)}}_{ij}; {\beta^{(1)}}_{ij}, {\beta^{(2)}}_{ij}, {\beta^{(3)}}_{ij}) \tag{2.6}$$

and

$$\breve{a}_j = ({\alpha^{(1)}}_j, {\alpha^{(2)}}_j, {\alpha^{(3)}}_j; {\beta^{(1)}}_j, {\beta^{(2)}}_j, {\beta^{(3)}}_j) \tag{2.7}$$

in triangular intuitionistic fuzzy numbers.

Step 3

Generate the weighted normalised fuzzy decision matrix. Linear scale transformation is used to convert many criterion scales into a common scale. This process produces the normalised IF decision matrix, denoted as $\check{N}$ and shown below:

$$N = [\check{n}_{ij}]_{r\times s}$$

Where,

$$\check{n}_{ij} = \left(\frac{\alpha_{ij}^{(1)}}{\alpha_{j^*}^{(3)}}, \frac{\alpha_{ij}^{(2)}}{\alpha_{j^*}^{(3)}}, \frac{\alpha_{ij}^{(3)}}{\alpha_{j^*}^{(3)}}; \frac{\beta^{(1)-}}{\beta_{ij}^{(3)}}, \frac{\beta^{(1)-}}{\beta_{ij}^{(2)}}, \frac{\beta^{(1)-}}{\beta_{ij}^{(1)}}\right) \tag{2.8}$$

with $\beta^{(1)-} = \min \beta_{ij}^{(1)}$and $\alpha_{j^*}^{(3)} = \max \alpha_{ij}^{(3)}$; for $j \epsilon C$and this denotes as benefit factor:

$$\check{n}_{ij} = \left(\frac{\alpha_j^{(1)-}}{\alpha_{ij}^{(3)}}, \frac{\alpha_j^{(1)-}}{\alpha_{ij}^{(2)}}, \frac{\alpha_j^{(1)-}}{\alpha_{ij}^{(1)}}; \frac{\beta^{(1)}{}_{ij}}{\beta_{j^*}^{(3)}}, \frac{\beta^{(2)}{}_{ij}}{\beta_{j^*}^{(3)}}, \frac{\beta^{(3)}{}_{ij}}{\beta_{j^*}^{(3)}}\right) \tag{2.9}$$

where $\alpha_j^{(1)-}$= min $\alpha_{ij}^{(1)}$and $\beta^{(3)}{}_j$= max $\beta^{(3)}{}_{ij}$; for $j \epsilon D$ this denotes as cost factor.

Step 4

Construct the weighted normalised intuitionistic fuzzy decision matrix. A weighted normalised IF decision matrix, denoted by $\check{Z}$, is created by multiplying a normalised IF decision matrix with an alternative rating as criterion weights. The weighted normalised IF decision matrix is given as follows: $Z = [\check{z}_{ij}]_{r\times s}$
where Ž can be computed by considering the weight of the criteria relevance as:

$$\check{z}_{ij} = \check{n}_{ij} \cdot \check{\alpha}_j \tag{2.10}$$

The weighted normalised IF decision matrix includes entries $\check{z}_{ij}$ (for all *i, j*) that reflect normalised TIFNs.

Step 5

Define the Intuitionistic Fuzzy Positive Ideal Solution (IFPIS) and Intuitionistic Fuzzy Negative Ideal Solution (IFNIS), then calculate the distance between each FPIS and FNIS option. The IFPIS is represented by A^*,while the IFNIS is represented by A^-. These terms are used from Step 4 to Step 5. Then it can be defined as:

$$A^* = (\check{z}_1^*, \check{z}_2^*, \dots, \check{z}_s^*),$$
$$z{\sim}j *= (\check{z}_1^-, \check{z}_2^-, \dots, \check{z}_s^-),$$

where,

$$\check{z}_j^* = \begin{cases} (1,1,1), (0,0,0)\, j \in C; \\ (0,0,0), (1,1,1)\, j \in \mathrm{D}. \end{cases}, \text{ for all } j=1,2,\dots,s$$

and

$$\check{z}_j^* = \begin{cases} (0,0,0), (1,1,1)\; j \in C; \\ (1,1,1), (0,0,0)\; j \in \mathrm{D}. \end{cases}, \text{ for all } j=1,2,\dots,s$$

In this phase, *C* considers the benefit key component, and *D* considers the cost factor form defined in Step 5.

Step 6

Measure the separation of all alternatives from IFPIS and IFNIS, respectively. Each alternative's separation from IFPIS A^* and IFNIS A^- can be calculated as follows:

$$Sp_i^* = \Sigma_{j=1}^{s} d(\check{z}_{ij}, \check{z}_j^*) \quad (2.11)$$

$$Sp_i^- = \Sigma_{j=1}^{s} d(\check{z}_{ij}, \check{z}_j^-) \quad (2.12)$$

for all $i=1,2, \dots, r$.

Step 7

Compute the closeness coefficient for all alternatives. After separating all alternatives A_i, ($i = 1, 2, \cdots, r$), the closeness coefficient can be defined as follows:

$$Cl.Coef_i = \frac{Sp_i^-}{Sp_i^- + Sp_i^*} \quad (2.13)$$

To calculate the closeness coefficient for each possibility, use the value of Sp_i^- *and* Sp_i^* in Step 6.

Step 8

Ranking of alternatives. Rank the alternatives in descending order based on the closeness coefficient to the ideal option. The higher the closeness coefficient, the better the alternative.

Statistical Analysis

To support and validate the fuzzy-based evaluation, several statistical analyses were conducted. These analyses enhance the robustness of the findings by assessing reliability, expectation–performance gaps and the consistency of consumer evaluations.

Reliability Analysis

Reliability analysis was performed using Cronbach's alpha to evaluate the internal consistency of items under each criterion. For social science research, a value of α larger than 0.70 is typically regarded as appropriate [18]. The computed reliability coefficients for the five criteria ranged from 0.75 to 0.88, indicating that the respondents' internal consistency was adequate.

Expectation–Performance Gap Analysis

To investigate differences between respondents' expectations and their perceptions of convenience shops' performance, an analysis between the expectation and performance gap study was carried out. This method, derived from the SERVQUAL framework [19], provides insight into whether each criterion meets, exceeds or falls short of consumer expectations. For each criterion, gap scores were computed as $Gap_j = P_j - E_j$, where *Pj* represents the mean performance score and *Ej* the mean expectation score. Positive values show the performance of the convenience store is above expectations, while negative values show underperformance.

Integration with TIF-TOPSIS Results

The statistical analyses actually complement the TIF-TOPSIS method by verifying consistency of the criteria ratings (reliability), while identifying consumer satisfaction gaps (expectation–performance), and contextualising the fuzzy rankings with descriptive insights. Together, these analyses strengthen the validity and interpretability of the final ranking outcomes obtained from TIF-TOPSIS method.

Implementation

This section comprises of two main components to provide a comprehensive analysis of the convenience store preferences. The first is the fuzzy implementation dan the second is the statistical implementation.

Fuzzy Implementation

This study was conducted to determine which convenience stores received the highest ratings from respondents. In this study, 70 decision-makers obtained, which it will be assigned as *DR1*, *DR2*, *DR3*, *DR4*, until *DR70*. Data on the importance weight of criteria and ratings of preference are given in Appendix A. Five alternatives involve namely as Store A (A_1), Store B (A_2), Store C (A_3), Store D (A_4), and Store E (A_5) with corresponding criterion involved were food cleanliness (C_1), store image (C_2), product assortment (C_3), price (C_4), and service quality (C_5).

Step 1

Sample of data for ratings and weight. By using the Equations (2.2) and (2.3), and data in Appendix A, the weights of the criteria and group ratings of the alternatives were determined respectively in all criteria for each of the alternatives (Tables 3 and 4). For both members and non-members, *C* represents criterion and *A* represents alternatives.

Table 3: The intuitionistic fuzzy weights of the five criteria

Criteria	C_1	C_2	C_3	C_4	C_5
ă	(0.80,0.94,0.99; 0.71,0.94,1.00)	(0.72,0.88,0.97; 0.63,0.88,0.98)	(0.66,0.83,0.95; 0.57,0.83,0.97)	(0.49,0.66,0.80; 0.40,0.66,0.85)	(0.77,0.92,0.98; 0.67,0.92,0.99)

Table 4: Ratings of alternatives in Intuitionistic Fuzzy (IF)

	C_1	C_2	C_3	C_4	C_5
A_1	(6.51,8.34,9.5; 5.65,8.34,9.69)	(6.26,8.04,9.2; 5.36,8.04,9.49)	(6.03,7.86,9.1; 5.21,7.86,9.44)	(4.53,6.37,7.97; 3.73,6.37,8.53)	(6.29,8.17,9.40; 5.41,8.17,9.62)
A_2	(6.69,8.46,9.5; 5.81,8.46,9.71)	(6.86,8.57,9.5; 5.96,8.57,9.75)	(6.77,8.50,9.5; 5.88,8.50,9.69)	(4.63,6.53,8.16; 3.84,6.53,8.67)	(5.97,7.83,9.11; 5.13,7.83,9.39)
A_3	(6.71,8.53,9.6; 5.81,8.53,9.76)	(6.80,8.51,9.5; 5.92,8.51,9.71)	(6.46,8.24,9.3; 5.59,8.24,9.61)	(6.80,8.51,9.53; 5.92,8.51,9.71)	(6.29,8.17,9.43; 5.42,8.17,9.66)
A_4	(6.57,8.39,9.5; 5.67,8.39,9.70)	(6.49,8.24,9.3; 5.65,8.24,9.61)	(6.51,8.29,9.4; 5.65,8.29,9.64)	(4.60,6.54,8.23; 3.80,6.54,8.77)	(6.20,8.07,9.33; 5.35,8.07,9.56)
A_5	(4.49,6.36,7.9; 3.64,6.36,8.48)	(4.39,6.21,7.8; 3.65,6.21,8.41)	(4.80,6.64,8.1; 4.01,6.64,8.59)	(5.20,7.06,8.50; 4.38,7.06,8.91)	(5.10,6.94,8.39; 4.29,6.94,8.80)

Step 2

From Equations 2.4 and 2.5, the decision-matrix is obtained as follows:

Ě=

$$
\begin{bmatrix}
(6.51,8.34,9.50; & (6.26,8.04,9.21; & (6.03,7.86,9.16; & (4.53,6.37,7.97; & (6.29,8.17,9.40; \\
5.65,8.34,9.69) & 5.36,8.04,9.49) & 5.21,7.86,9.44) & 3.73,6.37,8.53) & 5.41,8.17,9.62) \\
(6.69,8.46,9.53; & (6.86,8.57,9.57; & (6.77,8.50,9.51; & (4.63,6.53,8.16; & (5.97,7.83,9.11; \\
5.81,8.46,9.71) & 5.96,8.57,9.75) & 5.88,8.50,9.69) & 3.84,6.53,8.67) & 5.13,7.83,9.39) \\
(6.71,8.53,9.60; & (6.80,8.51,9.53; & (6.46,8.24,9.39; & (6.80,8.51,9.53; & (6.29,8.17,9.43; \\
5.81,8.53,9.76) & 5.92,8.51,9.71) & 5.59,8.24,9.61) & 5.92,8.51,9.71) & 5.42,8.17,9.66) \\
(6.57,8.39,9.50; & (6.49,8.24,9.39; & (6.51,8.29,9.41; & (4.60,6.54,8.23; & (6.20,8.07,9.33; \\
5.67,8.39,9.70) & 5.65,8.24,9.61) & 5.65,8.29,9.64) & 3.80,6.54,8.77) & 5.35,8.07,9.56) \\
(4.49,6.36,7.93; & (4.39,6.21,7.86; & (4.80,6.64,8.14; & (5.20,7.06,8.50; & (5.10,6.94,8.39; \\
3.64,6.36,8.48) & 3.65,6.21,8.41) & 4.01,6.64,8.59) & 4.38,7.06,8.91) & 4.29,6.94,8.80)
\end{bmatrix}
$$

$$\check{A} = \{(0.80, 0.94, 0.99 ; 0.71, 0.94, 1.00), (0.72, 0.88, 0.97 ; 0.63, 0.88, 0.98), (0.66, 0.83, 0.95 ; 0.57, 0.83, 0.97), (0.49, 0.66, 0.80 ; 0.40, 0.66, 0.85), (0.77, 0.92, 0.98 ; 0.67, 0.92, 0.99)\}$$

Step 3

Based on Equations (2.8) and (2.9), The normalised intuitionistic fuzzy decision matrix is presented in Table 5.

Table 5: The normalised of Intuitionistic Fuzzy Decision Making

	C_1	C_2	C_3	C_4	C_5
A_1	(0.68,0.87,0.99; 0.38,0.44,0.64)	(0.65,0.84,0.96; 0.38,0.45,0.68)	(0.63,0.83,0.96; 0.42,0.51,0.77)	(0.47,0.59,0.82; 0.39,0.67,0.89)	(0.67,0.87,1.00; 0.45,0.53,0.79)
A_2	(0.70,0.88,0.99; 0.37,0.43,0.63)	(0.72,0.90,1.00; 0.37,0.43,0.61)	(0.71,0.89,1.00; 0.41,0.47,0.68)	(0.46,0.57,0.81; 0.40,0.69,0.91)	(0.63,0.83,0.97; 0.46,0.55,0.84)
A_3	(0.70,0.89,1.00; 0.37,0.43,0.37)	(0.71,0.89,1.00; 0.38,0.43,0.62)	(0.68,0.87,0.99; 0.42,0.49,0.72)	(0.39,0.44,0.55; 0.62,0.89,1.02)	(0.67,0.87,1.00; 0.44,0.53,0.79)
A_4	(0.68,0.87,0.99; 0.38,0.43,0.64)	(0.68,0.86,0.98; 0.38,0.44,0.65)	(0.68,0.87,0.99; 0.42,0.48,0.71)	(0.45,0.57,0.81; 0.40,0.69,0.92)	(0.66,0.86,0.99; 0.45,0.53,0.80)
A_5	(0.47,0.66,0.83; 0.43,0.57,1.00)	(0.46,0.65,0.82; 0.43,0.59,1.00)	(0.50,0.70,0.86; 0.47,0.60,1.00)	(0.44,0.53,0.72; 0.46,0.74,0.93)	(0.54,0.74,0.89; 0.49,0.62,1.00)

Step 4

Using Equations (2.8) and (2.9), the weighted normalised Intuitionistic Fuzzy Decision Matrix is shown in Table 6.

Table 6: The weighted normalised Intuitionistic Fuzzy Decision Matrix

	C_1	C_2	C_3	C_4	C_5
A_1	(0.54,0.82,0.9; 0.27,0.41,0.64)	(0.47,0.74,0.9; 0.24,0.40,0.67)	(0.42,0.69,0.9; 0.24,0.42,0.75)	(0.23,0.39,0.6; 0.16,0.44,0.76)	(0.51,0.80,0.9; 0.30,0.48,0.79)
A_2	(0.56,0.83,0.9; 0.27,0.40,0.63)	(0.52,0.79,0.9; 0.24,0.37,0.60)	(0.47,0.74,0.9; 0.24,0.39,0.66)	(0.22,0.38,0.6; 0.16,0.45,0.77)	(0.49,0.76,0.9; 0.31,0.50,0.83)
A_3	(0.56,0.84,0.9; 0.26,0.40,0.63)	(0.51,0.78,0.9; 0.24,0.38,0.60)	(0.45,0.72,0.9; 0.24,0.40,0.70)	(0.19,0.29,0.4; 0.25,0.59,0.87)	(0.51,0.80,0.9; 0.30,0.48,0.78)
A_4	(0.55,0.82,0.9; 0.27,0.41,0.64)	(0.49,0.76,0.9; 0.24,0.39,0.63)	(0.45,0.72,0.9; 0.24,0.40,0.69)	(0.22,0.38,0.6; 0.16,0.45,0.78)	(0.51,0.79,0.9; 0.30,0.49,0.79)
A_5	(0.37,0.62,0.8; 0.30,0.54,1.00)	(0.33,0.57,0.8; 0.27,0.52,0.98)	(0.33,0.58,0.8; 0.27,0.50,0.97)	(0.22,0.35,0.57; 0.18,0.49,0.79)	(0.42,0.68,0.8; 0.33,0.57,0.99)

Step 5

In this study, the criteria such as food cleanliness, store image, product assortment and service quality were categorised as a benefit criterion while price as a cost criterion. In this case, the benefit criterion used is the component of (1,1,1; 0,0,0) while the cost criteria used is the component of (0,0,0; 1,1,1). The IFPIS (A^+) and IFNIS (A^-) are given as follows:

$$A^+ = ((1,1,1;0,0,0),(1,1,1;0,0,0),(1,1,1;0,0,0),(0,0,0;1,1,1),(1,1,1;0,0,0))$$
$$A^- = ((0,0,0;1,1,1),(0,0,0;1,1,1),(0,0,0;1,1,1),(1,1,1;0,0,0),(0,0,0;1,1,1))$$

Step 6

Based on Equation (2.11) for IFPIS and Equation (2.12) for IFNIS, the separation measure of each alternative is displayed in Table 7.

Table 7: Separation measure of each alternative

	IFPIS	**IFNIS**
A_1	2.24	3.62
A_2	2.16	3.68
A_3	2.05	3.79
A_4	2.18	3.67
A_5	2.76	3.20

Step 7

Based on Equation (2.13), the closeness coefficient is shown in Table 8.

Table 8: The relative closeness coefficient for each of the alternative

	Convenience Store	**Cl. Coef**	**Rank**
A_1	Store A	0.618	4
A_2	Store B	0.630	2
A_3	Store C	0.649	1
A_4	Store D	0.627	3
A_5	Store E	0.537	5

Step 8

Ranking of alternatives**.** By completing the closeness coefficient calculation, the results show Store C (A_3) rank first in the ranking of convenience stores with the highest value of closeness coefficient which is 0.649. Followed by the second, third and fourth was Store B (A_2), Store D (A_4), and Store A (A_1), respectively, while Store E (A_5) ranked last in the ranking of convenience stores with the lowest value of closeness coefficient which is 0.537. Table 9 represents the rank of convenience store in descending order.

$$A_3 \succ A_2 \succ A_4 \succ A_1 \succ A_5$$

Table 9: The rank of convenience store

	Convenience Store	Rank
A_3	Store C	1
A_2	Store B	2
A_4	Store D	3
A_1	Store A	4
A_5	Store E	5

Statistical Implementation

Step 1

Descriptive analysis. A total of 70 responses were collected from undergraduate students. The majority of respondents were aged 21 to 25 years, with a balanced distribution of gender. Most students reported visiting convenience stores on a weekly basis, while a smaller proportion reported rare visits. Out of the five convenience stores, Store B and Store A were the most well-liked, followed by Store C, Store D, and Store E. This profile demonstrates that young adult customers with a variety of shopping habits make up the majority of the sample.

Step 2

Reliability analysis**.** Table 10 displays the outcomes of Cronbach's alpha which was used to assess each construct's internal consistency of the questionnaire.

Table 10: Reliability analysis of constructs

Construct	Cronbach's α	Reliability Level
Cleanliness	0.84	Excellent
Store image	0.87	Excellent
Product assortment	0.84	Excellent
Price	0.75	Acceptable
Service quality	0.88	Excellent

All constructs recorded Cronbach's alpha values above 0.70, indicating reliable measurement and meeting the commonly accepted threshold for internal consistency [18, 20]. The criteria such as cleanliness, store image, product assortment, and service quality showed very strong internal consistency where α greater than 0.84. In contrast, the price construct demonstrated an adequate degree of reliability (α = 0.75), this indicates that students' perspectives on pricing were more diverse than those on other parameters.

Step 3

Gap analysis between expectation and performance. To further analyse the difference between expectation and performance, respondents were asked to score the convenience stores' perceived performance as well as their expectation of each criterion. The results in Table 11, reveal consistent expectation and performance gaps across most criteria.

Table 11: Expectation–performance gap analysis

Criterion	Expectation (Mean)	Performance (Mean)	Gap (E – P)
Cleanliness	4.51	3.77	0.74
Store image	4.16	3.75	0.41
Product assortment	3.87	3.73	0.14
Price	3.37	3.43	-0.06
Service quality	4.34	3.65	0.69

The positive value obtained from comparison between expectation and performance scores indicates that customers' expectations consistently exceeded their perceptions for four out of five criteria. The largest gaps were observed in cleanliness (0.74) and service quality (0.69). This highlights the importance of improving worker responsiveness and hygiene for all convenience stores, as customers place considerable emphasis on these two criteria. A moderate gap was also evident for store image (0.41), while product assortment (0.14) showed a relatively small shortfall. It is interesting to note that the price difference (-0.06) was very small, indicating that most students thought costs were either in line with or marginally better than their expectations.

According to these results, service delivery and cleanliness standards continue to be significant shortcomings that need to be fixed in order to better satisfy customers. Meanwhile, affordability is not a significant source of discontent.

Table 12: Store level gap analysis

Store	Biggest Weakness (Criterion)	Expectation (Mean)	Performance (Mean)	Gap (E–P)
Store E	Cleanliness	4.51	3.27	1.24
Store A	Cleanliness	4.51	3.83	0.69
Store B	Service Quality	4.34	3.66	0.69
Store C	Cleanliness	4.51	3.89	0.63
Store D	Service Quality	4.34	3.74	0.60

When compared at the shop level, the results for various brands revealed obvious flaws. Store E has the largest performance shortfall with a gap of 1.24 in cleanliness. This implies that important hygienic issues could have a significant impact on customer pleasure and trust. Store A and Store C also showed significant gaps in cleanliness (0.69 and 0.63, respectively). This suggesting that hygiene remains a key challenge for multiple operators. It also can be considered as importance factor for the customers. In contrast, Store B and Store D recorded their largest gaps in service quality (0.69 and 0.60, respectively), indicating that staff responsiveness and customer interaction represent the most pressing issues for these stores. When considered collectively, the results highlight that although pricing is generally in line with expectations, convenience stores should give priority to raising hygienic standards and improving service delivery in order to better meet customer expectations.

Step 4

Inferential statistics.

Table 13: Chi-square tests of association between demographics and store choice

Variable	χ^2	df	*p*-value
Gender × Store choice	1.64	3	0.65
Age group × Store choice	1.94	3	0.58

Table 14: ANOVA Results for service quality across demographics

Variable	F	df	*p*-value
Gender	0.32	1,68	0.58
Age group	5.40	1,68	0.023

Table 15: Post-hoc Tukey test for service quality by age group

Comparison	Mean Difference	*p*-value
18–20 vs. 21–25	-0.68	0.023

The most popular convenience store and demographic factors (gender and age) were compared using a chi-square test. The results indicated that gender ($\chi^2(3) = 1.64$, $p = 0.65$) and age group ($\chi^2(3) = 1.94$, $p = 0.58$) were not significantly related to store choice. This suggests that visit preferences were relatively consistent across demographic categories. In this study, there was no indicator that their preference is affected by gender and age.

Next to further examine differences in perceptions, ANOVA tests were performed on service quality ratings. The analysis showed no significant difference between genders, $F(1, 68) = 0.32$, $p = 0.58$, confirming that male and female respondents evaluated service quality similarly. However, a significant difference was observed across age groups, $F(1, 68) = 5.40$, $p = 0.023$. Post-hoc Tukey tests revealed that respondents aged 18–20 rated service quality significantly lower than those aged 21 to 25 years ($p = 0.023$). This suggests that younger students tend to be more critical of service quality compared to their older peers.

Step 5

Integration of statistical and fuzzy results. For integration with the fuzzy TIF-TOPSIS data, only the largest expectation-performance difference for each shop was considered. This method provides a clear connection between the fuzzy ranking results and the statistical validation by highlighting the most important region of dissatisfaction for each brand. By focusing on the single most critical vulnerability that each store needs to fix, highlighting the largest gap prevents clutter from numerous lesser gaps and provides a more practical viewpoint for managerial decision-making.

Table 16: Comparison of fuzzy rankings and largest expectation–performance gaps by store

Store	Fuzzy Rank	Biggest Gap (Statistical)	Gap Value
Store C	1 (Best)	Cleanliness	0.63
Store B	2	Service quality	0.69
Store D	3	Service quality	0.60
Store A	4	Cleanliness	0.69
Store E	5 (Less preferred)	Cleanliness	1.24

The integration of the statistical findings with the fuzzy TIF-TOPSIS results demonstrates a high degree of consistency between the two approaches. The fuzzy TIF-TOPSIS model ranked Store C as the best, also eexhibited comparatively small statistical gaps (Cleanliness = 0.63), demonstrating its excellent overall performance. Store B, which came in second, likewise shown mild deficiencies, with its biggest flaw being in service quality (0.69), indicating that staff responsiveness and customer contact still need to be improved. Additionally, Store D was ranked third in the fuzzy ranking also had a significant service quality gap (0.60), which is indicative of weaker customer-facing features that restrict its ability to compete. Despite being a well-known brand, Store A, which came in at number four, had the biggest cleanliness deficit (0.69). Lastly, Store E, which was continuously ranked lowest in both approaches, had the biggest overall statistical discrepancy (Cleanliness = 1.24), highlighting significant shortcomings in customer-facing qualities and hygiene.

Generally, these results demonstrate the complementary benefits of fuzzy rankings and statistical validation. While the fuzzy model establishes a distinct hierarchy of alternatives, the statistical gaps provide explanatory insight into the fundamental reasons of discontent. By highlighting cleanliness and service quality as the top targets for improvement, this integration guarantees more robust validation of the outcomes and better managerial guidance.

Conclusions

This study applied the Triangular Intuitionistic Fuzzy TOPSIS (TIF-TOPSIS) method to evaluate consumer preferences for convenience stores under subjective and uncertain conditions. The findings indicate that Store C ranked highest among the alternatives, followed by Store B, Store D, Store A, and Store E. The results show that service quality and cleanliness are the most influential criteria in shaping consumer preferences in the convenience store setting. The statistical analysis supports the fuzzy ranking outcomes by demonstrating consistent evaluation patterns among respondents. Stores with higher fuzzy rankings were also associated with smaller expectation–performance gaps, indicating better alignment with consumer expectations, while Store E showed comparatively larger gaps across both analyses. This agreement enhances the reliability and interpretability of the decision results. Overall, the study confirms that the TIF TOPSIS method is suitable for addressing subjective multi-criteria decision-making problems in a retail context. The combined fuzzy and statistical approach provides a clearer basis for interpreting results derived from uncertain inputs. Future studies may extend this work by applying alternative fuzzy decision-making methods or examining ranking stability across different respondent groups.

Authors' Contributions

All authors contributed to the study conception and design. All authors read and approved the final manuscript. Conceptualisation: Nazirah Ramli, Roselah Osman; Methodology: Nazirah Ramli, Roselah Osman, Suriyati Ujang; Formal analysis and investigation: Nazirah Ramli, Roselah Osman, Suriyati Ujang, Teguh Wibowo; Writing – original draft preparation: Nazirah Ramli, Roselah Osman, Nan Fatin Najihah, Suriyati Ujang; Writing – review and editing: Nazirah Ramli, Roselah Osman, Suriyati Ujang; Validation and visualisation: Nazirah Ramli, Roselah Osman, Suriyati Ujang, Teguh Wibowo; Supervision: Nazirah Ramli, Roselah Osman.

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Conflict of Interest Statement

The authors declare no conflict of interest.

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APPENDIX A

Table A (i): Importance Weights of the Criteria

CRITERIA	C1	C2	C3	C4	C5
DR1	VH	VH	H	VH	VH
DR2	VH	H	H	VH	H
DR3	H	H	H	M	H
DR4	VH	H	MH	M	H
DR5	MH	VH	MH	MH	VH

Table A (ii): Respondents' Ratings for All Criteria

CRITERIA	DR	A1	A2	A3	A4	A5
C1	DR1	G	G	G	G	MG
	DR2	G	VG	G	G	M
	DR3	G	G	G	G	M
	DR4	MG	MG	VG	G	M
	DR5	G	G	G	G	MP
C2	DR1	G	G	G	G	M
	DR2	G	VG	G	MG	G
	DR3	G	G	G	G	G
	DR4	M	M	G	G	M
	DR5	G	G	G	G	MG
C3	DR1	G	G	G	G	M
	DR2	G	VG	MG	G	M
	DR3	G	G	G	G	G
	DR4	MG	MG	G	G	M
	DR5	G	G	G	G	G
C4	DR1	MG	MG	G	MG	MG
	DR2	G	VG	G	VG	VP
	DR3	G	G	G	G	G
	DR4	M	M	G	MG	G
	DR5	M	MP	G	MP	M
C5	DR1	MG	MP	G	G	M
	DR2	G	VG	G	VG	VP
	DR3	G	G	G	G	G
	DR4	M	M	MG	MG	M
	DR5	M	M	MG	MG	M