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Fuzzy TOPSIS Application in Motorcycle Brand Rankings: A Preliminary Study

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ABSTRACT

Due to rapid economic growth, the demand for transportation has escalated, with cars and motorcycles being the most common personal vehicles. However, motorcycles have gained favor as a mode of transportation due to their ease of maneuvering through traffic, cost-effectiveness, and lower fuel consumption. Presently, there is a multitude of motorcycle manufacturers offering a diverse array of options. This study is focused on ascertaining the top motorcycle brand based on well-defined criteria, employing the fuzzy Technique for Order Preference by Similarity to Ideal Situation (fuzzy TOPSIS). Three expert decision makers were provided with a questionnaire to rank three motorcycle brands commonly used in Malaysia based on specific criteria: price, safety, efficiency, design, performance, and durability. Computational analyses were conducted, revealing Yamaha as the top-ranked brand with a closeness coefficient (CC) value of 0.2869, closely trailed by Honda with a CC of 0.2852. Modenas, on the other hand, ranked the lowest among the brands analyzed, with a CC of 0.1447. The marginal difference of 0.017 in CC between Yamaha and Honda suggests the highly competitive scenario between these two brands. By providing a comprehensive assessment of motorcycle brands, this study seeks to layout information of consumer preferences in decision making for motorcycle purchases. The preliminary results served as aid for manufacturers or retailers of the motorcycle market.

1. INTRODUCTION

Transportation is the deliberate movement of various entities, including goods, animals, and people, from one location to another. It plays a fundamental role in everyday life, connecting communities and facilitating trade. The efficiency and accessibility of transportation systems contribute significantly to the overall development and functioning of societies. Modes of transportation encompass automobiles, trains, buses, motorcycles, bicycles, and aircraft. In Malaysia, two-wheelers such as scooters and motorcycles are notably popular and dominant means of transportation. Despite the inherent drawbacks of motorcycles,

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such as exposure to extreme weather and limited safety features, the demand for motorcycles remains consistently high. Professor Dr. Kulanthayan K.C Mani, a road safety expert from Universiti Putra Malaysia, reported that motorcycles accounted for 46.6% of the total registered vehicles (Chan, 2022). Motorcycle ownership is significantly influenced by Income levels and fuel prices; however, the fluctuations in fuel price may not drastically affect the demand for motorcycles since they remain a cost-effective option (Ubaidillah, 2021). Malaysians opt to buy motorcycles for their ability to maneuver through traffic jams and reach their destinations swiftly. Various factors drive consumers to purchase motorcycles, including quality, trust, value, design, and practical usage. In addition, factors such as ease of use and discounts do not significantly influence customers in their decision to buy motorcycles (Ngantung, 2013). Walone (2016) reported that the most important criteria influencing consumers when choosing a motorcycle are product quality, followed by performance, price and sales promotion, with advertising being the least influential. A study by Sugandha et al. (2021) determined that customers' purchase intentions for Honda Genio are primarily influenced by product quality and brand image.

In Malaysia, motorcycles with engines below 125cc are the most prevalent type of motorcycles on the roads. Numerous brands, including Honda, Yamaha, Suzuki, Modenas, SYM, KTM Duke, and Benelli, offer motorcycles in this category. Although every motorcycle serves the same functionality, variations in price, safety features, and overall quality exist among them. The intense competition among manufacturers results in a wider range of choices for customers in terms of specifications, physical attributes, and product quality. This plethora of factors can complicate the decision-making process, especially for individuals with limited budgets, as they seek to ensure they make the best possible choice. Despite the alarming proportion of road traffic fatalities involving motorcycle accidents, motorcycles continue to reign as the most popular mode of transportation for courier services, food delivery, and daily commuting to work. Motorcycle safety technologies have been identified as a critical factor capable of reducing the incidence of fatal accidents among motorcyclists (Mokhtar et al.,2021).

The contribution of this study is two-fold. It addresses the gap in the understanding of motorcycle preferences, particularly within the Malaysian context. Secondly, it provides information about the criteria that influence the preference for a specific motorcycle brand. This study holds great significance for both motorcycle dealers and automotive manufacturers as it equips them with information to make informed decisions regarding manufacturing that aligns with consumer preferences. The primary objective of this paper was to rank three major motorcycle brands prevalent in the Malaysian market: Honda, Yamaha, and Modenas. This ranking was based on six important criteria: price, safety, efficiency, design, performance, and durability.

The paper is structured as follows: first, an analysis is conducted on the introduction of the problem and relevant literature, focusing on the most recent articles. The subsequent section thoroughly examines the methodology of multi-criteria decision-making (MCDM), known as fuzzy TOPSIS. The results of the study are detailed in the findings and discussion section. Finally, the conclusion, along with remarks and suggestions for future research, is presented in the last section.

2. METHODOLGY

In this study, we employed an MCDM approach known as fuzzy TOPSIS to rank three motorcycle brands based on specific criteria. The TOPSIS technique was originally developed by Hwang and Yoon in 1981, followed by further advancements by Yoon in 1987 and Hwang et al. in 1993. This technique involves selecting an alternative that is closest to the positive ideal solution (PIS) while being farthest from the negative ideal solution (NIS), making it an optimal choice. The PIS is composed of the best performance values for each alternative, often referred to as the benefit criteria, whereas the NIS consists of the worst performance values, known as the cost criteria. Since human decision-making inherently involves fuzziness and imprecision, the application of fuzzy set theory developed by Zadeh (1965) helps address this issue.

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Therefore, fuzzy TOPSIS emerges as a reliable and suitable decision-making tool, particularly in fuzzy environments where alternatives and criteria are expressed as linguistic variables.

The fuzzy TOPSIS method finds extensive application in various domains, including supplier selection, product ranking, and integration with other techniques. For instance, Senvar et al. (2016) integrated a hesitant fuzzy set into TOPSIS to select the optimal site for a new hospital in Istanbul. Barrios et al. (2017) devised a hybrid model by integrating the Analytic Hierarchy Process (AHP) and the TOPSIS method to select the most appropriate tomography equipment. Ertuğrul and Karakaşoğlu (2009) utilized the fuzzy AHP and TOPSIS to evaluate the performance of 15 Turkish cement firms listed on the Istanbul Stock Exchange. In both cases, the AHP was used to define the weight of each criterion, while TOPSIS was employed to assess the options. Roshandel et al. (2013) employed hierarchical fuzzy TOPSIS for supplier selection, a method initially introduced by Ates et al. (2006) to evaluate the performance of university professors' performance. This method extends fuzzy TOPSIS from three levels to four or more levels. Han and Trimi (2018) utilized fuzzy TOPSIS along with the Fuzzy Linguistic Decision Tools Enhancement Suite (FLINSTONES) software tool to generate aggregate scores for the assessment and evaluation of reverse logistics performance in social commerce platforms. Awasthi et al. (2011) applied fuzzy TOPSIS in evaluating a sustainable transportation system, producing aggregate scores for sustainability assessment and aiding in the selection of the best alternative. Similarly, Zulkifli et al. (2019) implemented fuzzy TOPSIS with input from three experts to rank insurance companies in Malaysia.

3. DATA COLLECTION

This study aims to explore motorcycle brand preferences in Malaysia, particularly in the rural area of Pokok Sena, Kedah. To achieve this, three decision makers with extensive knowledge of motorcycle brands were carefully selected to participate in the questionnaire. The questionnaire used in this study was adopted from Zulkifly et al. (2019). The chosen decision makers had more than five years of experience with various motorcycle brands, including two sales representatives and a mechanic. The study considered three motorcycle brands: two international brands, Honda and Yamaha, and one local brand, Modenas. The evaluation was based on six criteria: price, safety, efficiency, design, performance, and durability. The decision makers were tasked with evaluating the performance of the alternatives and indicating the importance of the criteria with linguistic variables. For performance evaluation, the linguistic variables used were "Very Poor" (VP), "Poor" (P), "Fair" (F), "Good" (G), and "Very Good" (VG). In representing the importance of the criteria, the linguistic variables used were "Very Low" (VL), "Low" (L), "Medium" (M), "High" (H), and "Very High" (VH). Each linguistic variable was assigned a value within the scales ranging from 1 to 9. The linguistic terms were then converted to fuzzy numbers, as shown in Table 1 (Sodhi & Prabhakar, 2012)

Table 1. Linguistic terms and triangular fuzzy numbers

Fuzzy Number	Performance of the Alternative	Importance of the Criteria
(1,1,3)	Very Poor (VP)	Very Low (VL)
(1,3,5)	Poor (P)	Low (L)
(3,5,7)	Fair (F)	Medium (M)
(5,7,9)	Good (G)	High (H)
(7,9,9)	Very Good (VG)	Very High (VH)

The following are some basic definitions and properties in the context of fuzzy logic.

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Definition 1 If X is a universe of discourse and x is a particular element of X, then a fuzzy set A defined on X can be written as a collection of ordered pairs $\left(x, \mu_{\tilde{A}}(x)\right)$;
$A = \left\{ \left(x, \mu_{\tilde{A}}(x)\right) : x \in A \right\}$, where $\mu_{\tilde{A}}(x)$ is a membership function that defines the fuzzy set.

Definition 2 A triangular membership function is defined by three parameters $\{a, b, c\}$, where *a*, *b*, and *c* represent the *x* coordinates of the three vertices of $\mu_{\tilde{A}}(x)$ in a fuzzy set A. *a* and *c* correspond to the lower and upper boundaries, respectively, both having a membership degree of 0, while *b* indicates the point with a membership degree of 1. A triangular fuzzy number is represented as $\tilde{a} = (a, b, c)$ and is defined as the following:

$$\mu_{\tilde{a}}(x) = \begin{cases} \dfrac{x-a}{b-a} & \text{if } a \le x \le b \\ \dfrac{c-x}{c-b} & \text{if } b \le x \le c \\ 0 & \text{Otherwise} \end{cases}$$

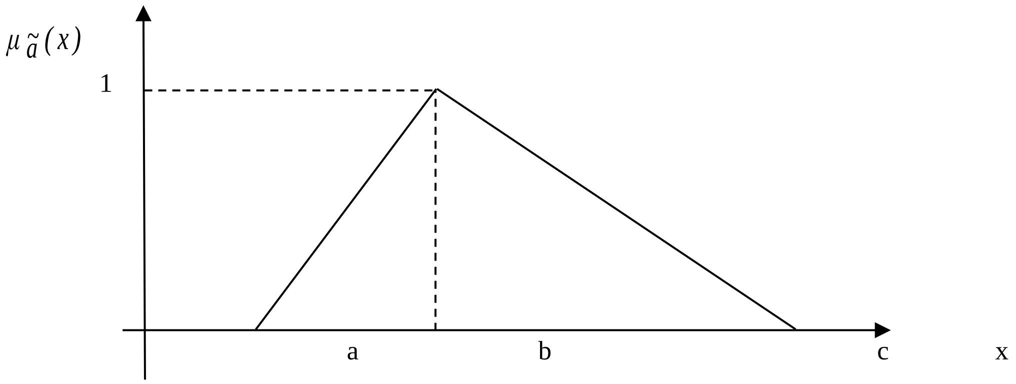

Fig.1: A triangular fuzzy number $\tilde{a}$

Let $\tilde{a} = (a_1, b_1, c_1)$ and $\tilde{b} = (a_2, b_2, c_2)$ be two triangular fuzzy numbers.

Definition 3 The multiplication of $\tilde{a}$ and $\tilde{b}$ is given by:

$$\tilde{a} \times \tilde{b} = (a_1 a_2, b_1 b_2, c_1 c_2) \tag{1}$$

Definition 4 The distance between $\tilde{a}$ and $\tilde{b}$ is given by:

$$d(\tilde{a}, \tilde{b}) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]} \tag{2}$$

3.1 Fuzzy Technique for Order Preference by Similarity to Ideal Situation (Fuzzy TOPSIS)

The measurement procedures of fuzzy TOPSIS typically involves the following steps.

Step 1. Collect the subjective evaluations of the decision makers on the importance of weight.
Let's say there are k decision makers, the fuzzy rating by the k^{th} decision maker about the i^{th} alternative on the j^{th} criterion is given as $\tilde{x}_{ij}^{k} = \left(a_{ij}^{k}, b_{ij}^{k}, c_{ij}^{k}\right)$. Meanwhile, the importance weight given by the k^{th} decision maker regarding the i^{th} alternative on the j^{th} criterion is given by $\tilde{w}_{j}^{k} = \left(a'^{k}_{ji}, b'^{k}_{ji}, c'^{k}_{ji}\right)$, where $i = 1,2,\ldots,m$, and $j = 1,2,\ldots,n$.

Step 2. Calculate the aggregate fuzzy ratings based on the decision makers' subjective evaluations.
The aggregated fuzzy ratings $\tilde{x}_{ij}$ for alternatives i with respect to each criterion j are given by $\tilde{x}_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right)$, where

$$a_{ij} = \min_{k}\left\{a_{ij}^{k}\right\}, \quad b_{ij} = \frac{1}{K}\sum_{k=1}^{K} b_{ij}^{k}, \quad c_{ij} = \max_{k}\left\{c_{ij}^{k}\right\}, \tag{3}$$

The aggregated fuzzy weights for each criterion are calculated as $\tilde{w}_{j}^{k} = \left(a'^{k}_{ji}, b'^{k}_{ji}, c'^{k}_{ji}\right)$, where

$$a'^{k}_{ji} = \min_{k}\left\{a'^{k}_{ji}\right\}, \quad b'_{ji} = \frac{1}{K}\sum_{k=1}^{K} b'^{k}_{ji}, \quad c'_{ji} = \max_{k}\left\{c'^{k}_{ji}\right\}, \tag{4}$$

Step 3. Generate the fuzzy decision matrix.
A fuzzy MGDM problem, briefly expressed in matrix format, can be represented as follows:

$$\tilde{X} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & & C_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ \\ A_m \end{array} & \begin{pmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \ldots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \ldots & \tilde{x}_{2n} \\ \ldots & \ldots & \tilde{x}_{ij} & \ldots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \ldots & \tilde{x}_{mn} \end{pmatrix} \end{array}$$

$$\tilde{W} = \left(\tilde{w}_1, \tilde{w}_2, \ldots, \tilde{w}_n\right)$$

where for all $\tilde{x}_{ij}$ and $\tilde{x}_{j}, i = 1,2,\ldots,m; j = 1,2,\ldots,n$. Here, $\tilde{x}_{ij} = \left(a_{ij}, b_{ij}, c_{ij}\right)$ and $\tilde{w}_{j} = \left(a'_{j}, b'_{j}, c'_{j}\right)$ are triangular fuzzy numbers representing linguistic variables.

Step 4. Normalize the decision matrix.
Construct the normalized fuzzy decision matrix and consider $\tilde{R}$ as the normalized fuzzy decision matrix.

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{m \times n}, i = 1,2,\ldots,m; \; j = 1,2,\ldots,n.$$

The normalized values for benefit and cost criteria are:

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$$\tilde{r}_{ij}^{+} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right) \quad \text{(Benefit Criteria)} \tag{5}$$

$$\tilde{r}_{ij}^{-} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right) \quad \text{(Cost Criteria)} \tag{6}$$

where $c_j^* = \max\{c_{ij}\}$ for benefit criteria and $a_j^- = \min\{a_{ij}\}$ for cost criteria.

Step 5. Construct the weighted normalized fuzzy decision matrix.

The weighted normalized fuzzy decision matrix $\tilde{V}$ is computed by multiplying the weights of j^{th} criteria $(\tilde{w}_j)$ with the normalized fuzzy decision matrix $\tilde{r}_{ij}$ as:

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m\times n},\ i = 1,2,\ldots,m;\ j = 1,2,\ldots,n \text{ where } \tilde{v}_{ij} = \tilde{r}_{ij} \times \tilde{w}_h = \left(a_{ij}'', b_{ij}'', c_{ij}''\right) \tag{7}$$

Step 6. Define the fuzzy positive ideal solution (FPIS) F^+ and fuzzy negative solution (FNIS) F^- .
The FPIS and FNIS of the alternatives are defined as follows:

$$F^+ = \left(\tilde{v}_1^+, \tilde{v}_2^+, \ldots, \tilde{v}_n^+\right) \text{ where } \tilde{v}_j^+ = (1,1,1)$$

$$F^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-\right) \text{ where } \tilde{v}_j^- = (0,0,0)$$

Step 7. Calculate the distance from FNIS and FPIS for each alternative.
The distance d_i^+ and d_i^- of each weighted alternative $i = 1,2,\ldots,m$ from both FPIS and FNIS is computed as follows:

$$d_i^+ = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}^+, 1\right) \qquad i = 1,2,3\ldots,m \qquad \text{(Benefit criteria)} \tag{8}$$

$$d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}^-, 0\right) \qquad i = 1,2,3\ldots,m \qquad \text{(Cost criteria)} \tag{9}$$

Where $d(\tilde{a}, \tilde{b})$ is the distance measurement between two fuzzy numbers $\tilde{a}$ and $\tilde{b}$ calculated using equation (2). In this calculation, the maximum value of $\tilde{v}_{ij}^+$ in each alternative is chosen for benefit criteria while the minimum value of $\tilde{v}_{ij}^-$ is chosen for cost criteria.

Step 8. Calculate the closeness coefficient (CC_i) for each alternative.
The formula below represents the closeness coefficient for each alternative:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+}, \qquad i = 1,2,\ldots,m \tag{10}$$

Step 9. Rank the alternatives.
The alternatives are ranked with respect to CC_i in decreasing order. The highest CC_i represents the FPIS, which signifies the best alternative, being close to 1. Conversely, the FNIS is farthest from 0.

4. RESULTS AND DISCUSSION

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As previously mentioned, this study employed six distinct criteria to evaluate three motorcycle brands, identified as alternatives, specifically Yamaha (A1), Honda (A2), and Modenas (A3). The selected criteria encompass price (C1), safety (C2), efficiency (C3), design (C4), performance (C5), and durability (C6). These specific attributes were thoughtfully chosen from a pool of 20 attributes, a selection curated by Ngantung (2013), with a keen eye on their pertinence within the Malaysian context. To conduct this evaluation, three decision makers were deliberately chosen, each of whom was interviewed and subsequently participated in the completion of a detailed questionnaire. This decision-making panel consisted of two motorcycle sellers and a skilled mechanic residing in Pokok Sena, Kedah. Their extensive knowledge and experience encompassed all facets of the three motorcycle brands under consideration.

The data collected from the decision makers regarding the evaluation of alternatives against the criteria are summarized in Table 2. The decision makers evaluated the criteria and alternatives based on the linguistic term presented in Table 1. Additionally, Table 3 illustrates the evaluation provided by the decision makers concerning the criteria themselves.

Table 2. The collected data from the decision makers regarding the assessment of alternatives against the criteria (DMi)

Criteria	**A1**			**A2**			**A3**		
	DM1	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**	**DM1**	**DM2**	**DM3**
C1	G	G	G	G	VG	VG	G	F	F
C2	G	G	G	VG	G	F	G	P	G
C3	G	VG	VG	G	G	G	G	F	F
C4	VG	G	G	G	G	F	F	P	VG
C5	G	G	G	VG	G	G	F	F	G
C6	G	VG	F	VG	G	VG	F	F	P

Table 3. The collected data provided by the decision makers (DMi) pertaining to the criteria themselves

Criteria	**DM1**	**DM2**	**DM3**
C1	VH	H	L
C2	H	VH	H
C3	H	VH	H
C4	VH	VH	H
C5	H	VH	H
C6	VH	VH	VH

The next step involved calculating the aggregated fuzzy weight for each alternative with respect to each criterion, as well as the aggregated fuzzy weight for each criterion. These computations were conducted using equations (3) and (4). The outcomes of these calculations are presented in Tables 4 and 5, respectively. The aggregation is important for multi criteria decision making which it processes the decision makers' input.

Table 4. Aggregate fuzzy weights of the alternatives

		A1	A2	A3
C1	DM1	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
	DM2	(5, 7, 9)	(7, 9, 9)	(3, 5, 7)
	DM3	(5, 7, 9)	(7, 9, 9)	(3, 5, 7)
Aggregate Rating		**(5, 7, 9)**	**(5, 8.333, 9)**	**(3, 5.667, 9)**
C2	DM1	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)
	DM2	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)
	DM3	(5, 7, 9)	(3, 5, 7)	(5, 7, 9)
Aggregate Rating		**(5, 7, 9)**	**(3, 7, 9)**	**(1, 5.667, 9)**

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	DM1	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
C3	DM2	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)
	DM3	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)
Aggregate Rating		**(5, 8.333, 9)**	**(5, 7, 9)**	**(3, 5.667, 9)**
	DM1	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)
C4	DM2	(5, 7, 9)	(5, 7, 9)	(1, 3, 5)
	DM3	(5, 7, 9)	(3, 5, 7)	(7, 9, 9)
Aggregate Rating		**(5, 7.667, 9)**	**(3, 6.333, 9)**	**(1, 5.667, 9)**
	DM1	(5, 7, 9)	(7, 9, 9)	(3, 5, 7)
C5	DM2	(5, 7, 9)	(5, 7, 9)	(3, 5, 7)
	DM3	(5, 7, 9)	(5, 7, 9)	(5, 7, 9)
Aggregate Rating		**(5, 7, 9)**	**(5, 7.667, 9)**	**(3, 5.667, 9)**
	DM1	(5, 7, 9)	(7, 9, 9)	(3, 5, 7)
C6	DM2	(7, 9, 9)	(5, 7, 9)	(3, 5, 7)
	DM3	(3, 5, 7)	(7, 9, 9)	(1, 3, 5)
Aggregate Rating		**(3, 7, 9)**	**(5, 8.333, 9)**	**(1, 4.333, 7)**

Table 5. Aggregate fuzzy weights of the criteria

Criteria	Decision Makers			Aggregate Fuzzy Weight
	DM1	**DM2**	**DM3**	
C1	(7, 9, 9)	(5, 7, 9)	(1, 3, 5)	**(1, 6.333, 9)**
C2	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	**(5, 7.667, 9)**
C3	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	**(5, 7.667, 9)**
C4	(7, 9, 9)	(7, 9, 9)	(5, 7, 9)	**(5, 8.333, 9)**
C5	(5, 7, 9)	(7, 9, 9)	(5, 7, 9)	**(5, 7.667, 9)**
C6	(7, 9, 9)	(7, 9, 9)	(7, 9, 9)	**(7, 9, 9)**

The decision matrices were consolidated for both the aggregate fuzzy alternative (*X*) and weightage (*W*), as depicted below.

$$X = \begin{bmatrix} (5,7,9) & (5,8.333,9) & (3,5.667,9) \\ (5,7,9) & (3,7,9) & (1,5.667,9) \\ (5,8.333,9) & (5,7,9) & (3,5.667,9) \\ (5,7.667,9) & (3,6.333,9) & (1,5.667,9) \\ (5,7,9) & (5,7.667,9) & (3,5.667,9) \\ (3,7,9) & (5,8.333,9) & (1,4.333,7) \end{bmatrix}$$

$$W = \begin{bmatrix} (1,6.333,9) \\ (5,7.667,9) \\ (5,7.667,9) \\ (5,8.333,9) \\ (5,7.667,9) \\ (7,9,9) \end{bmatrix}$$

The following step entailed constructing the normalized decision matrix for both benefit and cost attributes using equations (5) and (6) correspondingly. The outcomes of these calculations are presented in Table 6 and Table 7. A sample calculation for (A1, C1) is demonstrated below.

$$\tilde{r}^{+}_{11} = \left(\frac{5}{9}, \frac{7}{9}, \frac{9}{9}\right) = (0.556, 0.778, 1)$$

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Table 6. Normalized fuzzy decision matrix (benefit criteria)

	A1	A2	A3
C1	(0.556, 0.778, 1)	(0.556, 0.926, 1)	(0.333, 0.630, 1)
C2	(0.556, 0.778, 1)	(0.333, 0.778, 1)	(0.111, 0.630, 1)
C3	(0.556, 0.926, 1)	(0.556, 0.778, 1)	(0.333, 0.630, 1)
C4	(0.556, 0.852, 1)	(0.333, 0.704, 1)	(0.111, 0.630, 1)
C5	(0.556, 0.778, 1)	(0.556, 0.704, 1)	(0.333, 0.630, 1)
C6	(0.333, 0.778, 1)	(0.556, 0.926, 1)	(0.111, 0.481, 0.778)

$$R^{+}=\begin{bmatrix}(0.556,0.778,1) & (0.556,0.926,1) & (0.333,0.630,1)\\ (0.556,0.778,1) & (0.333,0.778,1) & (0.111,0.630,1)\\ (0.556,0.926,1) & (0.556,0.778,1) & (0.333,0.630,1)\\ (0.556,0.852,1) & (0.333,0.704,1) & (0.111,0.630,1)\\ (0.556,0.778,1) & (0.556,0.704,1) & (0.333,0.630,1)\\ (0.333,0.778,1) & (0.556,0.926,1) & (0.111,0.481,0.778)\end{bmatrix}$$

$$\tilde{r}^{-}_{11}=\left(\frac{3}{5},\ \frac{3}{7},\ \frac{3}{9}\right)=(0.6,0.429,0.333)$$

Table 7. Normalized fuzzy decision matrix (cost criteria)

	A1	A2	A3
C1	(0.6, 0.429, 0.333)	(0.6, 0.36, 0.333)	(0.333, 0.176, 0.111)
C2	(0.6, 0.429, 0.333)	(1, 0.429, 0.333)	(1, 0.176, 0.111)
C3	(0.6, 0.36, 0.333)	(0.6, 0.429, 0.333)	(0.333, 0.176, 0.111)
C4	(0.6, 0.391, 0.333)	(1, 0.474, 0.333)	(1, 0.176, 0.111)
C5	(0.6, 0.429, 0.333)	(0.6, 0.391, 0.333)	(0.333, 0.176, 0.111)
C6	(1, 0.429, 0.333)	(0.6, 0.36, 0.333)	(1, 0.231, 0.143)

$$R^{-}=\begin{bmatrix}(0.6,0.429,0.333) & (0.6,0.36,0.333) & (0.333,0.176,0.111)\\ (0.6,0.429,0.333) & (1,0.429,0.333) & (1,0.176,0.111)\\ (0.6,0.36,0.333) & (0.6,0.429,0.333) & (0.333,0.176,0.111)\\ (0.6,0.391,0.333) & (1,0.474,0.333) & (1,0.176,0.111)\\ (0.6,0.429,0.333) & (0.6,0.391,0.333) & (0.333,0.176,0.111)\\ (1,0.429,0.333) & (0.6,0.36,0.333) & (1,0.231,0.143)\end{bmatrix}$$

The weighted normalized fuzzy decision matrix for the benefit and cost criteria was calculated using equation (7). The results are presented in Tables 8 and 9, respectively.

$$\bar{V}^{+}_{11}=(0.556,0.778,1)\ X\ (1,6.333,9)=(0.556,4.926,9)$$

Table 8. Weighted normalized fuzzy decision matrix (benefit criteria)

	A1	A2	A3

https://doi.org/10.24191/jcrinn.v9i1

C1	(0.556, 4.926, 9)	(0.556, 5.864, 9)	(0.333, 3.988, 9)
C2	(2.778, 5.963, 9)	(1.667, 5.963, 9)	(0.556, 4.828, 9)
C3	(2.778, 7.099, 9)	(2.778, 5.963, 9)	(1.667, 4.828, 9)
C4	(2.778, 7.099, 9)	(1.667, 5.864, 9)	(0.556, 5.247, 9)
C5	(2.778, 5.963, 9)	(2.778, 6.531, 9)	(1.667, 4.828, 9)
C6	(2, 5.963, 9)	(3.333, 7.099, 9)	(0.667, 3.691, 9)

$$V^+ = \begin{bmatrix} (0.556, 4.926, 9) & (0.556, 5.864, 9) & (0.333, 3.988, 9) \\ (2.778, 5.963, 9) & (1.667, 5.963, 9) & (0.556, 4.828, 9) \\ (2.778, 7.099, 9) & (2.778, 5.963, 9) & (1.667, 4.828, 9) \\ (2.778, 7.099, 9) & (1.667, 5.864, 9) & (0.556, 5.247, 9) \\ (2.778, 5.963, 9) & (2.778, 6.531, 9) & (1.667, 4.828, 9) \\ (2, 5.963, 9) & (3.333, 7.099, 9) & (0.667, 3.691, 9) \end{bmatrix}$$

$$\bar{V}^-_{11} = (0.6, 0.429, 0.333)\ X\ (1, 6.333, 9) = (0.6, 2.714, 3)$$

Table 9. Weighted normalized fuzzy decision matrix (cost criteria)

	A1	A2	A3
C1	(0.6, 2.714, 3)	(0.6, 2.28, 3)	(0.333, 1.118, 1)
C2	(3, 3.286, 3)	(5, 3.286, 3)	(5, 1.353, 1)
C3	(3, 2.76, 3)	(3, 3.286, 3)	(1.667, 1.353, 1)
C4	(3, 3.261, 3)	(5, 3.947, 3)	(5, 1.47, 1)
C5	(3, 3.286, 3)	(3, 3, 3)	(1.667, 1.353, 1)
C6	(6, 3.286, 3)	(3.6, 2.76, 3)	(6, 1.769, 1.286)

$$V^- = \begin{bmatrix} (0.6, 2.714, 3) & (0.6, 2.28, 3) & (0.333, 1.118, 1)) \\ (3, 3.286, 3) & (5, 3.286, 3) & (5, 1.353, 1) \\ (3, 2.76, 3) & (3, 3.286, 3) & (1.667, 1.353, 1) \\ (3, 3.261, 3) & (5, 3.947, 3) & (5, 1.47, 1) \\ (3, 3.286, 3) & (3, 3, 3) & (1.667, 1.353, 1) \\ (6, 3.286, 3) & (3.6, 2.76, 3) & (6, 1.769, 1.286) \end{bmatrix}$$

In Table 10, the distances from FNIS and FPIS for both benefit and cost criteria of each alternative were depicted using equations (8) and (9). The distance value indicates the closeness of the criteria. It is worth noting that for this study, the FPIS value was standardized to [1,1,1], while the FNIS was set at [0,0,0], adhering to Chen's method (Chen,2000).

$$d^+(\tilde{V}^+_{11}, 1) = \sqrt{\frac{1}{3}[(2.778 - 1)^2 + (7.099 - 1)^2 + (9 - 1)^2]} = 5.867$$

$$d^-(\tilde{V}^-_{11}, 0) = \sqrt{\frac{1}{3}[(0.6 - 0)^2 + (2.714 - 0)^2 + (3 - 0)^2]} = 2.361$$

Table 10. Distance measurements of d^+ (benefit) and d^- (cost)

	A1	A2	A3

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d^+ (benefit)	5.867	5.962	5.243
d^- (cost)	2.361	2.379	0.887

Finally, the CC for each alternative was computed using equation (10), enabling the determination of their respective rankings based on these coefficients.

Table 11. Closeness coefficient values and ranking of alternatives

Alternative	CC_i	Rank
A1	0.2869	1
A2	0.2852	2
A3	0.1447	3

Based on the findings presented in Table 11, it can be concluded that Yamaha secured the top rank with a CC value of 0.2869, closely followed by Honda with a CC value of 0.2852. Modenas, on the other hand, obtained a CC value of 0.1447, positioning it last in the ranking. Notably, the CC values for Yamaha and Honda displayed a marginal difference of only 0.017, indicating a highly competitive scenario between these two brands. The primary reason for Yamaha securing the top spot can be attributed to its exceptional durability and performance, which is particularly beneficial in the agricultural setting of Pokok Sena. This area, located 20 km east of the capital city Alor Star, Kedah, is predominantly engaged in rice cultivation and rubber plantation, making Yamaha's suitability for heavy-duty activities a pivotal factor. These findings align with Walone (2016), which identified Yamaha as the most preferred motorcycle brand in Manado, one of the cities in Indonesia. Following Yamaha, Honda emerged as the second most preferred brand, with Suzuki securing the third position in preference.

5. CONCLUSION

In conclusion, considering the critical criteria of price, safety, efficiency, design, performance, and durability, Yamaha emerged as the top-ranked brand, closely followed by Honda and Modenas. It is important to note that the results are context-specific to the decision makers from Pokok Sena, Kedah, and may not be universally applicable to other locations. Given Pokok Sena's agricultural reliance and preference for small-sized motorcycles due to its predominantly farming-based economy, this study essentially focused on such motorcycle types. An intriguing avenue for future research lies in examining motorcycle rankings in urban settings like Kuala Lumpur and George Town, where usage patterns and preferences may significantly differ. Expanding the scope of analysis to include additional brands, criteria, and sub-criteria would enrich the assessment. In this study, fuzzy TOPSIS was employed, favoring alternatives closer to the FPIS and distant from the FNIS. For comprehensive insights, employing other MCDM techniques like fuzzy elimination and choice expressing reality (fuzzy ELECTRE), fuzzy Delphi method (FDM), and preference ranking organization method for enrichment evaluation (PROMETHEE) is recommended.

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7. CONFLICT OF INTEREST STATEMENT

The authors agree that this study was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

8. AUTHORS' CONTRIBUTIONS

Muhammad Nur Ikmal Nooralam carried out the research, wrote and revised the article. Zurina Kasim supervised the research progress. Zurina Kasim the review, revisions and approved the article submission.

9. REFERENCES

Ateş, N. Y., Çevik, S., Kahraman, C., Gülbay, M., & Erdoğan, S. A. (2006). Multi attribute performance evaluation using a hierarchical fuzzy TOPSIS method. In Kahraman, C. (Ed.), *Fuzzy applications in industrial engineering. Studies in Fuzziness and Soft Computing* (pp. 537-572). Springer. https://doi.org/10.1007/3-540-33517-X_22

Awasthi, A., Chauhan, S. S., & Omrani, H. (2011). Application of fuzzy TOPSIS in evaluating sustainable transportation systems. *Expert Systems with Applications, 38*(10), 12270–12280. https://doi.org/10.1016/j.eswa.2011.04.005

Barrios, M. A. O., De Felice, F., Negrete, K. P., Romero, B. A., Arenas, Y., & Petrillo, A. (2016). An AHP-TOPSIS integrated model for selecting the most appropriate tomography equipment. *International Journal of Information Technology & Decision Making*, *15*(4), 861 - 885.

Chan, D. (2022, June 9). *Vehicles outnumber people in Malaysia. New Strait Times.* https://www.nst.com.my/news/nation/2022/06/803654/vehicles-outnumber-people-malaysia

Chen, C. T. (2000). Extensions of the TOPSIS for group decision-making under fuzzy environment. *Fuzzy sets and systems*, *114*(1), 1-9.

Ertuğrul, I., & Karakaşoğlu, N. (2009). Performance evaluation of Turkish cement firms with fuzzy analytic hierarchy process and TOPSIS methods. *Expert Systems with Applications*, *36*(1), 702–715. https://doi.org/10.1016/j.eswa.2007.10.014

Hwang, C.L., Lai, Y.J., & Liu, T.Y. (1993). A new approach for multiple objective decision making. *Computers & Operations Research*, *20*(8), 889-899.

Hwang, C.L. & Yoon, K. (1981). *Multiple Attribute Decision Making: Methods and applications*. Springer-Verlag, New York. http://dx.doi.org/10.1007/978-3-642-48318-9

Han, H., & Trimi, S. (2018). A fuzzy TOPSIS method for performance evaluation of reverse logistics in social commerce platforms. *Expert Systems with Applications*, *103*, 133–145. https://doi.org/10.1016/j.eswa.2018.03.003

https://doi.org/10.24191/jcrinn.v9i1

Mokhtar, N.H., Hamzah,L., Mamat, H.C., Nasir, M.Z.N., Mamat, M.F. (2021). Decreasing the rate of motorcycle accidents in malaysia: Analytical hierarchy process approach. *The 3rd Symposium on Industrial Science and Technology (SISTEC2021)*, 2682(1). AIP Publishing. https://doi.org/10.1063/5.0114323

Ngantung N. V. (2013). Determinant factors of product attributes to consumer buying behavior of motorcycles. *Journal of Linguistic Studies*, *1*(4), 697–707.

Roshandel, J., Miri-Nargesi, S. S., & Hatami-Shirkouhi, L. (2013). Evaluating and selecting the supplier in detergent production industry using hierarchical fuzzy TOPSIS. *Applied Mathematical Modelling*, *37*(24), 10170–10181. https://doi.org/10.1016/j.apm.2013.05.043

Senvar, O., Otay, I., & Bolturk, E. (2016). Hospital Site Selection via Hesitant Fuzzy TOPSIS. *IFAC-PapersOnLine*, *49*(12), 1140–1145. https://doi.org/10.1016/j.ifacol.2016.07.656

Sodhi, B., & Prabakar, T.V. (2012). *A simplified description of Fuzzy TOPSIS.* ArXiv, abs/1205.5098.

Sugandha, A. P., Bella, C. M. ., & Indarwati, T. (2021). Analysis of factors affecting consumer intention to buy Honda Genio Motorcycles. *International Journal of Economics, Management, Business, and Social Science (IJEMBIS)*, *1*(2), 226–232. https://doi.org/10.59889/ijembis.v1i2.28

Ubaidillah, N.Z.(2021). An Econometric Analysis of Motorcycle Demand in Sarawak, Malaysia. *ABAC Journal Assumption University*, *41* (2), 121-136.

Walone, L. N. (2016). Analyzing the consumer purchase intention in selecting motorcycle brand using analytical hierarchy process (AHP) approach. *Jurnal Berkala Ilmiah Efisiensi*, *16*(3).

Zadeh, L. A. (1965). Fuzzy Sets. *Information and Control*, *8*, 338-353.

Zulkifly, N. A. Q., Kasim, Z., & Bidin, J. (2019). Selection of personal medical and health insurance company by using FUZZY TOPSIS. *Jurnal Intelek*, *14*(1), 36-46.