A Decision Support System for Assessing and Prioritizing Sustainable Urban Transportation in Metaverse

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***Abstract*— Blockchain technology and metaverse advancements allow people to create virtual personalities and spend time online. Integrating public transportation into the metaverse could improve services and collect user data. This study introduces a hybrid decision-making framework for prioritizing sustainable public transportation in Metaverse under q-rung orthopair fuzzy set (q-ROFS) context. In this regard, firstly q-rung orthopair fuzzy (q-ROF) generalized Dombi weighted aggregation operators (AOs) and their characteristics are developed to aggregate the q-ROF information. Second, a q-ROF information-based method using the removal effects of criteria (MEREC) and stepwise weight assessment ratio analysis (SWARA) models are proposed to find the objective and subjective weights of criteria, respectively. Then, a combined weighting model is taken to determine the final weights of the criteria. Third, the weighted sum product (WISP) method is extended to q-ROFS context by considering the double normalization procedures, the proposed operators and integrated weighting model. This method has taken the advantages of two normalization processes and four utility measures that approve the effect of benefit and cost criteria by using weighted sum and weighted product models. Next, to demonstrate the practicality and effectiveness of the presented method, a case study of sustainable public transportation in metaverse is presented in the context of q-ROFSs. The findings of this study confirms that the proposed model can recommend more feasible performance while facing numerous influencing factors and input uncertainties, and thus, provides a wider range of applications.**

***Index Terms*— Metaverse, Sustainable public transport, Q-rung orthopair fuzzy set, Generalized Dombi operators, MEREC, SWARA, WISP.**

I. Introduction

The advancements in metaverse technology have been rapid. This enabled the metaverse to be more easily and quickly integrated into our lives. The COVID-19 pandemic has accelerated the realization of the metaverse's potential because telecommuting and education were conducted virtually to avoid contact with each other [1-3]. Metaverse is a virtual medium with blockchain innovations that ensures data privacy [4]. Many companies and organizations have recently invested in the metaverse [5-6]. As the metaverse became more popular, transportation needs grew. Implementing public transportation and micro-mobility systems into the metaverse has become more important. Climate change is another global issue, so sustainable transportation systems are crucial [7-9]. This issue has made sustainability important because world preservation is crucial. Transportation is a major source of carbon emissions [10]. Many decision-makers prioritize sustainable transportation systems. Metaverse data collection makes enhancing and innovating sustainable transportation systems easier and more legitimate. According to a previous study, origin information of public transportation users is easily collected with traditional methods, but destination information is mostly unknown because passengers' exit locations are not collected [11]. Integrating metaverse into real-life activities including public transportation allows the collection of origin and destination data through avatars, which aids public transportation optimization. In the long term, metaverse applications will be virtual, making people's daily activities virtual. So, cities will be more sustainable with less transportation demand. In a study regarding the use of micro-mobility modes, it is stated that the use of these modes has the potential to decrease short-distance travel made with personal vehicles, which contributes to the sustainability of transportation systems [12-14]. Hence, implementing these modes such as bicycles, and e-scooters into the metaverse is promising as means of achieving sustainable public transportation.

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A. Fuzzy sets for multi-criteria decision making

In the realistic decision making process, due to the ambiguity and intangibility arising from human qualitative opinions, experts' judgments cannot be exactly expressed by crisp numbers. The concept of fuzzy set (FS) [15] has widely been introduced as a powerful mathematical tool for solving vague and uncertain problems in human assessments and decisions. Orthopair fuzzy sets are FSs wherein the membership function of an element 'y' are pairs of values $(\mu(y), \nu(y))$ in the interval [0,1], where $\mu(y)$ and $\nu(y)$represent the support *for* and *against* memberships in the FS, respectively. Due to increasing complexity of the realistic information, Yager [16] pioneered a general class of these sets called q-rung orthopair fuzzy sets (q-ROFSs). In q-ROFS, the sum of the q^{th} powers of support for and against should be smaller than or equal to unity. It is clear that as q increases the acceptable space of orthopairs will increase and this geometric range offers more freedom to the decision experts (DEs) while articulating their preferences, thoughts, and judgments. Thus, q-ROFS can be considered a generalization of the IFS, PFS and FFS, and therefore provides a wider range to express the uncertain information. Zeng et al. [17] presented a model by combining weighted induced logarithmic distance measure to solve the MCDM problems with q-ROFS information. In this regard, they firstly studied the counter-intuitive cases of existing distance measures and then introduced a new measure of induced logarithmic distance with its desirable properties. Deveci et al. [18] proposed a hybridized q-ROF information-based MCDM framework for ranking the safe e-scooter operation alternatives. Liang et al. [19] constructed a novel tri-reference point (TRP) model for solving q-ROFS-based MCDM problem by considering the interaction of criteria with Bayesian network. Saha et al. [20] presented the q-ROF-"full consistency method (FUCOM)"-"double normalization-based multi-aggregation (DNMA)" approach to deal with the "healthcare waste treatment technology (HCWTT)" assessment.

It is observed from the existing literature that there are various MCDM approaches whose computational processes are based on "weighted sum model (WSM)" or "weighted product model (WPM)" or their combined form. In addition, there is a variation in the normalization processes employed, and also the procedures of handling the impact of cost and benefit criteria. Inspired by MULTIMOORA, CoCoSo and WASPAS methods, Stanujkic et al. [21] proposed an innovative MCDM method, named as simple Weighted Sum Product (WISP), which is based on WSM and WPM. In comparison with the existing methods, the WISP approach utilizes much easier normalization process, employs four utility measures for determining the overall utility of alternatives, and provides a simpler way to rank the alternatives. However, the classical WISP method has a single normalization process for treating the benefit and cost criteria, which would bias the outcomes because of the fault normalized values for aggregation.

B. Motivation

From the brief review, the following challenges can be identified which motivated this study:

1. In the literature, the criteria weights are categorized into objective and subjective weights. The objective weights are estimated from the decision matrices and are acquired based on the information provided by the DEs. Whilst the subjective weights notify the subjective opinions of the DEs regarding the relative significance of criteria. Few research efforts [23-24] have made to derive the objective and subjective weights of criteria under q-ROFS context. However, existing objective weighting models rarely consider the removal effects of criteria on alternatives' performances as a measure for weighting from q-ROF perspective.
2. In the literature [25-30], there is no study regarding the combination of objective and subjective criteria weights within q-ROFS setting, while a hybridized weight-determining model based on the objective and subjective weighting models can surmount the disadvantages which occur either in an objective weighting model or in a subjective weighting model.
3. The utility value-based techniques such as TOPSIS, VIKOR, WASPAS, SMART, CoCoSo and MULTIMOORA have the benefits of the simple calculation, easy to understand and rank the alternatives in an easiest way. These advantages make them become the most commonly used MCDM techniques in realistic situations. As compared with TOPSIS, WASPAS, VIKOR, CoCoSo and MULTIMOORA, the WISP is one of the novel and valuable utility theory-based methods for prioritizing the alternatives in a more easy and usable way. However, the classical WISP [21] and intuitionistic fuzzy WISP [31] have limitations in using onefold normalization procedure, which would mislead the decision outcomes. To the best of authors' information, the classical WISP technique with double normalization procedure has not been considered for solving MCDM problems under q-ROFS context.

C. Novelty and research contributions

Notable contributions and highlights of the proposed study are as follows:

1. In the literature, it is observed that there are only very few studies that investigate the effects, possibilities, and know-how of implementing public transportation systems in the metaverse. Therefore, this study is unique in means of providing a guide to decision-makers in the stage of implementing public transportation systems into the metaverse.
2. To aggregate the q-ROF information, this paper extends the generalized Dombi operators under q-ROFS context and proposes the q-ROF generalized Dombi weighted averaging and geometric aggregation operators (AOs) with their enviable properties.
3. This study introduces an integrated weighting model with the combination of objective weighting model based on MEREC approach and subjective weighting model based on SWARA method to derive the combined criteria weights from q-ROF perspective.
4. The WISP approach is extended to the q-ROFS context by considering the double normalization procedure, the proposed q-ROF generalized Dombi AOs and the hybridized criteria weight-determining model, which can

better describe the uncertain evaluation information and avoid information loss.

D. Organization of the paper

The remainder of this study is organized as follows: Section II presents the concepts relevant to the proposed approach. Section III introduces some generalized Dombi AOs for q-ROFSs and discusses their characteristics. Section IV proposes a hybrid WISP model for solving MCDM problems under highly uncertain context. Section V gives the problem definition. Section VI presents the case study of sustainable public transportation in Metaverse. In addition, this section discusses sensitivity and comparative analyses. Section VII presents the discussion of the results. Finally, Section VIII discusses the concluding remarks and future research scopes.

II. Preliminaries

Here, we present the basic concepts related to the q-ROFS and generalized Dombi operator.

Definition 1 [16]. A q-ROFS U on a finite universal set $\Upsilon=\{y_1,y_2,...,y_n\}$ is described as follows:

$$U=\{(y_i,\mu_U(y_i),\nu_U(y_i))|\, y_i\in\Upsilon\}, \quad (1)$$

where $\mu_U:\Upsilon\to[0,1]$ and $\nu_U:\Upsilon\to[0,1]$ symbolize the degrees of membership and non-membership of an object $y_i\in\Upsilon$, respectively with the conditions $0\le\mu_U(y_i)\le 1,\ 0\le\nu_U(y_i)\le 1,$ $0\le(\mu_U(y_i))^q+(\nu_U(y_i))^q\le 1,$ $q\ge 1,\ \forall\, y_i\in\Upsilon.$ For each $y_i\in\Upsilon$, the hesitancy function is presented by $\pi_U(y_i)=\sqrt[q]{1-(\mu_U(y_i))^q-(\nu_U(y_i))^q},\ \forall\, y_i\in\Upsilon.$ For convenience, "q-ROF number (q-ROFN)" is denoted by $\omega=(\mu,\nu)$.

Definition 2 [32]. For a q-ROFN $\omega=(\mu,\nu)$, the score and accuracy degrees are defined as

$$\mathrm{S}(\omega)=\frac{1}{2}\left(\left(\mu^q-\nu^q+\left(\frac{\exp(\mu^q-\nu^q)}{\exp(\mu^q-\nu^q)+1}-\frac{1}{2}\right)\pi^q\right)+1\right). \quad (2)$$

Definition 3 [22]. The generalized Dombi operator $GDom_p^q$, developed by Dombi [22] is defined by the following expression

$$GDom_\beta^\alpha(x_1,x_2)=\left(1+\left(\frac{1}{\beta}\left(\prod_{i=1}^{2}\Phi_\beta^\alpha(x_i)-1\right)\right)^{-\frac{1}{\alpha}}\right)^{-1}, \quad (3)$$

or $$GDom_\beta^\alpha(x_1,x_2)=\left(1+\left(\frac{1}{\beta}\left(\prod_{i=1}^{2}\Omega_\beta^\alpha(x_i)-1\right)\right)^{\frac{1}{\alpha}}\right)^{-1} \quad (4)$$

with $\Omega_\beta^\alpha(x_i)=1+\beta\left(\frac{x_i}{1-x_i}\right)^q,\ \Phi_\beta^\alpha(x_i)=1+\beta\left(\frac{1-x_i}{x_i}\right)^q,\ \beta>0$ $x_i\in(0,1),\ i=1,2,$ and $\alpha\ge 1.$

III. Generalized Dombi operators on q-ROFNs

Here, we firstly present some generalized Dombi operations on q-ROFNs. Motivated by the q-ROF generalized Dombi operations, we introduce q-ROF generalized Dombi weighted averaging and geometric operators and their desirable characteristics.

A. q-ROF-generalized Dombi weighted averaging (q-ROFGDWA) operator

This section proposes a novel q-ROFGDWA operator to fuse the q-rung orthopair fuzzy information.

Definition 4. Consider $\omega_i=(\mu_i,\nu_i),\ i=1,2,...,r$ be a set of q-ROFNs. Then the q-ROFGDWA operator is defined by

$$q-ROFGDWA(\omega_1,\omega_2,...,\omega_r)=(\varphi_1\,\omega_1)\tilde{\oplus}(\phi_2\,\omega_2)\tilde{\oplus}...\tilde{\oplus}(\varphi_r\,\omega_r), \quad (5)$$

where $\varphi_i\,(i=1(1)r)$ denotes the weight of ω_i satisfying $\sum_{i=1}^{r}\varphi_i=1.$

Theorem 1. Suppose $\omega_i=(\mu_i,\nu_i),\ i=1,2,...,r$ be a set of q-ROFNs. Then the aggregated value $q-ROFGDWA(\omega_1,\omega_2,...,\omega_r)$ is also a q-ROFN, where

$$q-ROFGDWA(\omega_1,\omega_2,...,\omega_r)=\left(\left(1+\left(\frac{1}{\beta}\left(\prod_{i=1}^{r}(\Omega_\beta^\alpha(\mu_i))^{\varphi_i}-1\right)\right)^{-\frac{1}{\alpha}}\right)^{\frac{-1}{q}},\left(1+\left(\frac{1}{\beta}\left(\prod_{i=1}^{r}(\Phi_\beta^\alpha(\nu_i))^{\varphi_i}-1\right)\right)^{\frac{1}{\alpha}}\right)^{\frac{-1}{q}}\right). \quad (6)$$

Proof. It follows from Definitions 4.

B. q-ROF-generalized Dombi weighted geometric (q-ROFGDWG) operator

Here, we extend the generalized Dombi weighted geometric operator to q-ROFSs and introduce the q-ROFGDWG operator.

Definition 5. Consider $\omega_i=(\mu_i,\nu_i),\ i=1,2,...,r$ be a set of q-ROFNs. Then the q-ROFGDWG operator on q-ROFNs is defined by

$$q-ROFGDWG(\omega_1,\omega_2,...,\omega_r)=(\omega_1^{\varphi_1})\tilde{\otimes}(\omega_2^{\varphi_2})\tilde{\otimes}...\tilde{\otimes}(\omega_r^{\varphi_r}), \quad (7)$$

where $\varphi_i\,(i=1(1)r)$ represents the weight of ω_i with $\sum_{i=1}^{r}\varphi_i=1.$

Theorem 2. Assume that $\omega_i=(\mu_i,\nu_i),\ i=1,2,...,r$ be a set of q-ROFNs. The aggregated value $q-ROFGDWG(\omega_1,\omega_2,...,\omega_r)$ is also a q-ROFN and

$$q-ROFGDWG(\omega_1,\omega_2,...,\omega_r)=\left(\left(1+\left(\frac{1}{\beta}\left(\prod_{i=1}^{r}(\Phi_\beta^\alpha(\mu_i))^{\varphi_i}-1\right)\right)^{\frac{1}{\alpha}}\right)^{\frac{-1}{q}},\left(1+\left(\frac{1}{\beta}\left(\prod_{i=1}^{r}\left(\Omega_\beta^\alpha(\nu_i)\right)^{\varphi_i}-1\right)\right)^{-\frac{1}{\alpha}}\right)^{\frac{-1}{q}}\right). \quad (8)$$

Proof: It follows from Definition 5.

IV. Proposed q-ROF-MEREC-SWARA-DN-WISP method

Here, we propose a new double normalization-based integrated weighted sum-product (DN-WISP) method with q-ROF generalized Dombi weighted AOs, the MEREC and the SWARA approaches, and named as q-ROF-MEREC-SWARA-DN-WISP framework. The calculation process of developed q-ROF-MEREC-SWARA-DN-WISP method is specified as follows:

Step 1: Create the "linguistic decision matrix (LDM)".

For MCDM problems on q-ROFSs setting, consider the sets of alternatives $\{T_1, T_2, ..., T_m\}$ and criteria/ attributes $\{r_1, r_2, ..., r_n\}$. A team of "decision experts (DEs)" $\{g_1, g_2, ..., g_l\}$ presents the evaluation rating of each alternative T_i over the criterion r_j in form of "linguistic values (LVs)". Assume that $M = \left(\chi_{ij}^{(k)}\right)_{m\times n} = \left(\mu_{ij}^{(k)}, \nu_{ij}^{(k)}\right)_{m\times n}$, $i = 1,2,...,m, j = 1,2,...,n$ be a "linguistic decision-matrix (LDM)" given by the DEs, where $\chi_{ij}^{(k)}$ specifies the evaluation rating of an alternative T_i concerning a criterion r_j for k^{th} DE.

Step 2: Derive the weights of DEs

To determine the DEs' weights, first of all the importance degrees of the DEs are considered as LVs and then expressed by q-ROFNs. To compute the k^{th} DE, let $g_k = (\mu_k, \nu_k)$ be the q-ROFN. Now, the expert weight is obtained by

$$\varpi_k = \frac{1}{2}\left(\frac{\left(\mu^q - \nu^q + \left(\frac{\exp(\mu^q - \nu^q)}{\exp(\mu^q - \nu^q)+1} - \frac{1}{2}\right)\pi^q + 1\right)}{\sum_{k=1}^{\ell}\left(\mu^q - \nu^q + \left(\frac{\exp(\mu^q - \nu^q)}{\exp(\mu^q - \nu^q)+1} - \frac{1}{2}\right)\pi^q + 1\right)} + \frac{l - r_k + 1}{\sum_{k=1}^{\ell}(l - r_k + 1)}\right), \quad (9)$$

Here, r_k is the rank of DEs, $\varpi_k \geq 0$ and $\sum_{k=1}^{\ell}\varpi_k = 1$.

Step 3: Build the "aggregated q-ROF-DM (A-q-ROF-DM)"

To make the A-q-ROF-DM, all individual q-ROF-DM assessments entail to be merged into one group. To ease this, the q-ROFGDWA or q-ROFGDWG operator is used on $M = \left(\chi_{ij}^{(k)}\right)_{m\times n}$ and obtained $Z = \left(z_{ij}\right)_{m\times n}$, where

$$z_{ij} = \left(\mu_{ij}, \nu_{ij}\right) = q - ROFGDWA_{\varpi}\left(\chi_{ij}^{(1)}, \chi_{ij}^{(2)}, ..., \chi_{ij}^{(\ell)}\right)$$

$$\text{or} \quad z_{ij} = \left(\mu_{ij}, \nu_{ij}\right) = q - ROFGDWG_{\varpi}\left(\chi_{ij}^{(1)}, \chi_{ij}^{(2)}, ..., \chi_{ij}^{(\ell)}\right). \quad (10)$$

Step 4: Calculate the criteria weights by q-ROF-MEREC-SWARA method.

To determine the criteria weights by integrating the objective and subjective weighting, the q-ROF-MEREC-SWARA is applied in this step.

Case I: Objective weights determination by q-ROF-MEREC.

The q-ROF-MEREC model involves the following steps:

Step 4a: Find the score matrix $\Theta = \left(\beta_{ij}\right)_{m\times n}$ of each q-ROFN ς_{ij}, where

$$\beta_{ij} = \frac{1}{2}\left(\left(\mu^q - \nu^q + \left(\frac{\exp\left(\mu^q - \nu^q\right)}{\exp\left(\mu^q - \nu^q\right)+1} - \frac{1}{2}\right)\pi^q\right) + 1\right). \quad (11)$$

Step 4b: Determine the overall performance value of each alternative. By means of the score values, we can certify that smaller degree of β_{ij} yield higher degrees of performance as follows:

$$\vartheta_i = ln\left(1 + \left(\frac{1}{n}\sum_j\left|ln\left(\beta_{ij}\right)\right|\right)\right). \quad (12)$$

Step 4c: Estimate the assessment degree of each alternative by eliminating each criterion. Let us consider ϑ'_{ij} be the overall performance of i^{th} alternative regarding the elimination of j^{th} criterion. The assessment procedure is presented as

$$\vartheta'_{ij} = ln\left(1 + \left(\frac{1}{n}\sum_{k, k\neq j}\left|ln\left(\beta_{ik}\right)\right|\right)\right). \quad (13)$$

Step 4d: The sum of absolute deviation is represented by Abd_j and is defined by

$$Abd_j = \sum_i\left|\vartheta'_{ij} - \vartheta_i\right|. \quad (14)$$

Step 4e: The objective weights of the criteria is denoted by w_j^M and obtained in the following expression:

$$w_j^M = \frac{Abd_j}{\sum_{j=1}^{n} Abd_j}. \quad (15)$$

Case II: Subjective weights evaluation by SWARA method

Step 4f: Apply Eq. (2) to obtain the score values $S\left(z_{kj}\right)$ for diverse criteria. Afterwards, the comparative significance $\left(c_j\right)$ is obtained with the use of j^{th} and $(j\text{-}1)^{\text{th}}$ positions attribute.

Step 4g: Estimate the comparative coefficient using the Eq. (16):

$$k_j = \begin{cases} 1, & j = 1, \\ c_j + 1, & j > 1. \end{cases} \quad (16)$$

Step 4h: Using Step 4i, we obtain the recalculated weight d_j as follows:

$$d_j = \begin{cases} 1, & j = 1, \\ \frac{k_{j-1}}{k_j}, & j > 1. \end{cases} \quad (17)$$

Step 4i: Obtain the subjective weight as follows:

$$w_j^S = \frac{d_j}{\sum_{j=1}^{n} d_j}. \quad (18)$$

Case III: Estimate the integrated weight using Eq. (15) and Eq. (18) as follows:

$$w_j = \gamma\, w_j^M + (1-\gamma)\, w_j^S, \quad (19)$$

where $\gamma \in [0,1]$ signifies the decision-precision coefficient.

Step 5: Assessment of the normalized A-q-ROF-DM

Here, we discuss linear and vector normalization formulae. Both the numerical values and q-ROFNs are managed by these formulae.

Step 5a: The linear normalization removes the dimensions of attributes using the principle with the interval maximum-minimum [33-34]. A linear normalization procedure is defined by

$$\square^{(1)} = \left(\eta_{ij}^{(1)}\right)_{m\times n} = \left(\bar{\mu}_{ij}^{(1)}, \bar{\nu}_{ij}^{(1)}\right) = \frac{z_{ij}}{\max_i \mathrm{S}\left(z_{ij}\right)}, \tag{20}$$

where $\mathrm{S}(.)$ is a score function of q-ROFNs.

Step 5b: The vector normalization has been used to normalize the A-q-ROF-DM $\square = \left(z_{ij}\right)_{m\times n}$, as $\square^{(2)} = \left(\eta_{ij}^{(2)}\right)_{m\times n}$, where $\eta_{ij}^{(2)} = \left(\bar{\mu}_{ij}^{(2)}, \bar{\nu}_{ij}^{(2)}\right)$,

such that $$\bar{\mu}_{ij}^{(2)} = \frac{\mu_{ij}}{\left(\sum_{i=1}^{m}\left\{\left(\mu_{ij}\right)^2\right\}\right)^{1/2}}, \quad \bar{\nu}_{ij}^{(2)} = \frac{\nu_{ij}}{\left(\sum_{i=1}^{m}\left\{\left(\nu_{ij}\right)^2\right\}\right)^{1/2}}. \tag{21}$$

Due to the fact that both the vector and linear normalization hold some benefits and restrictions, simultaneously [35-37], they are combined here using various AOs in a way to achieve various utility degrees of alternatives.

Step 6: Calculate the weighted sum deviation (WSD) and weighted sum ratio (WSR) measures using linear normalization

We firstly define the combined assessment degree based on the q-ROFGDWA operator for beneficial and non-beneficial as

$$s_i^{+} = q - ROFGDWA\left(\eta_{i1}^{(1)}, \eta_{i2}^{(1)}, \ldots, \eta_{in}^{(1)}\right), \tag{22}$$

$$s_i^{-} = q - ROFGDWA\left(\eta_{i1}^{(1)}, \eta_{i2}^{(1)}, \ldots, \eta_{in}^{(1)}\right). \tag{23}$$

Next, we define the WSD and WSR measures based on score values of combined assessment degree as follows:

$$s_i^{d} = \mathrm{S}^*\left(s_i^{+}\right) - \mathrm{S}^*\left(s_i^{-}\right), \tag{24}$$

$$s_i^{r} = \begin{cases} \mathrm{S}^*\left(s_i^{+}\right) / \mathrm{S}^*\left(s_i^{-}\right), & when\ r_b \cap r_n \neq \varnothing, \\ \mathrm{S}^*\left(s_i^{+}\right), & when\ r_n = \varnothing, \\ 1/\mathrm{S}^*\left(s_i^{-}\right), & when\ r_b = \varnothing. \end{cases} \tag{25}$$

Step 7: Calculate the weighted product deviation (WPD) and weighted product ratio (WPR) measures using vector normalization

We apply the vector normalization values to put forward the second aggregation measure by the q-ROFGDWG operator for beneficial and non-beneficial as

$$p_i^{+} = q - ROFGDWG\left(\eta_{i1}^{(2)}, \eta_{i2}^{(2)}, \ldots, \eta_{in}^{(2)}\right), \tag{26}$$

$$p_i^{-} = q - ROFGDWG\left(\eta_{i1}^{(2)}, \eta_{i2}^{(2)}, \ldots, \eta_{in}^{(2)}\right). \tag{27}$$

Now, we define the WPD and WPR measure based on score values of second aggregation measure as follows:

$$p_i^{d} = \mathrm{S}^*\left(p_i^{+}\right) - \mathrm{S}^*\left(p_i^{-}\right). \tag{28}$$

$$p_i^{r} = \begin{cases} \mathrm{S}^*\left(p_i^{+}\right) / \mathrm{S}^*\left(p_i^{-}\right), & when\ r_b \cap r_n \neq \varnothing, \\ \mathrm{S}^*\left(p_i^{+}\right), & when\ r_n = \varnothing, \\ 1/\mathrm{S}^*\left(p_i^{-}\right), & when\ r_b = \varnothing. \end{cases} \tag{29}$$

Step 8: Estimate the modified utility degree of each alternative

The modified values of utility measures are defined as follows:

$$u_i^{sd} = \frac{1 + s_i^{d}}{1 + \max_i s_i^{d}}, \tag{30}$$

$$u_i^{sr} = \frac{1 + s_i^{r}}{1 + \max_i s_i^{r}}, \tag{31}$$

$$u_i^{pd} = \frac{1 + p_i^{d}}{1 + \max_i p_i^{d}}, \tag{32}$$

$$u_i^{pr} = \frac{1 + p_i^{r}}{1 + \max_i p_i^{r}}. \tag{33}$$

Step 9: Compute the overall utility degree (OUD) u_i of each alternative by using Eq. (34)

$$u_i = \frac{1}{4}\left(u_i^{sd} + u_i^{sr} + u_i^{pd} + u_i^{pr}\right), \text{ where } u_i \in [0,1]. \tag{34}$$

Step 10: In accordance with the values of OUD, prioritize the alternatives and choose the optimal one.

V. Problem Definition

High population and urbanization cause transportation challenges. Peak hour traffic, for example, might cause physical and mental issues. Metaverse technology can reduce or eliminate peak-hour traffic. Metaverse technology enables effective, sustainable transportation. Concerns remain regarding how this technology will be applied in public transit [38]. In this research, decision-makers examine the implications of the metaverse on sustainable public transportation.

A. Definition of Alternatives

T_1: Incorporating the operation of public transport into the metaverse (e.g., optimization of the operation, demand planning, routing, lines, etc.): With Metaverse, fewer people will need to travel to work or public institutions because they can do their work remotely. While public vehicle demand is reduced, the metaverse can help manage it. Digital control and monitoring of public transport structures is possible [39]. Origin data, which indicates where bus passengers board, is easily collected by Automated Data Collection (ADC) systems [11]. Passenger destination data is difficult to collect because it's unknown where passengers leave the vehicles. Incorporating metaverse applications into real-life public transportation systems and using avatars to collect transportation data makes it easier to collect more complete origin and destination information from passengers. In this alternative, people travel in real life, but metaverse apps collect transit data.

T_2. Integrating e-car-sharing, e-scooter, and e-sharing economy into the metaverse (e.g. encouraging the use of sharing economy for sustainable transportation): The sharing economy, which refers to temporary use of a product or service, is growing as consumer habits change. Vehicle tracking, control, charging, and redistribution can be done digitally, and credit card-based payment services will accept metaverse-created avatars. This alternative involves real-world sharing economy applications. Metaverse technologies in sharing economy applications help owners monitor vehicles and users pay with avatars. This integration allows metaverse users to take hologram-like car-sharing trips.

T_3: Promoting innovation and advancement in sustainable technologies to manage transportation demand (e.g., virtual products and experiences): With transparent metaverse data, traffic demand can be monitored regionally and temporally, and

transportation planners can make more accurate decisions. By planning and implementing transportation infrastructure according to user needs, time costs could be reduced and people's ability to participate in economic movements increased [40]. Short-term, metaverse applications will be integrated into real-life activities, as in T1 and T2. Long-term, with advances in metaverse applications, workplaces, schools, etc. will be virtual. People will use this virtual medium from home for many daily tasks. This reduces transportation needs and improves sustainability. Unlike T1 and T2, this alternative's metaverse applications are virtual.

B. Definition of Criteria

(1) Social Sustainability Aspect

r_1: Providing an inclusive and equal universe (benefit): Access to alternative transportation will increase people's life participation. Access to social opportunities requires demand- and need-based public transportation [41].

r_2: Reduced data privacy issue (cost): As the integration of technology with the transportation sector increases, sharing of people’s travel and personal data with service providers becomes a necessity, requiring greater security measures [42].

r_3: Giving large corporations control of our transportation choices (cost): Large companies monopolize the shared transportation sector and prioritize economics over social concerns. For these reasons, an accessible transportation infrastructure cannot be built [43].

(2) Environmental Aspect

r_4: NFT — (Non-Fungible Token) side effects (cost): NFT transforms blockchain-based physical items into virtual items in Metaverse. Virtual items are traded using blockchain-based cryptocurrencies. NFT production emits carbon, and future problems due to increased production are unknown [44].

r_5: Hardware essential requirements competing with EV production (cost): Chips, one of the most important components of Metaverse, may cause competition in supplying electric vehicle manufacturers interested in sustainability. Slowing the transition to electric vehicles will disrupt the transition to a sustainable transportation sector [45].

r_6: The carbon footprint of AI training (cost): In the studies, it was determined that the artificial intelligence used with 213 million parameters was equal to 626,155 pounds of CO_2, while it was observed that an effect equal to 78000 pounds of CO_2 occurred in the 6-month tests performed with the 4789 model [46].

(3) Efficiency Aspect

r_7: Reduced use of resources (e.g., telecommuting reduces the expenses in the companies for the office) (benefit): In Metaverse, some of the public services or private company services will be carried out remotely. It is estimated that there will be a decrease in the consumption of natural resources due to the decrease in the production needed [47].

r_8: Increased energy use (cost): With the spread of the metaverse, it is expected that there will be an increase in the amount of energy consumed by people, especially from growing data centers and factories producing the equipment and hardware [48].

r_9: The transition from local data centers to the cloud (benefit): Due to the Metaverse's decentralized structure, participation requires storing vast amounts of data in the cloud. One study estimated that data centers accounted for 2% of global greenhouse gas emissions in 2015, the same as the aviation industry. This requires more data centers, which consume a lot of electricity, but it also forces more local data centers to move to the cloud, which may be environmentally friendly [49-50].

(4) Livability Aspect

r_{10}: improved quality of life for residents (benefit): In Metaverse, the ability to handle things remotely will reduce the amount of travel for people and enable them to access services more quickly and easily [51].

r_{11}: providing functionally dense and green city (benefit): With fewer cars, business and social activities will replace parking spaces, improving city life. More smart, green cities are expected [52].

VI. EXPERIMENTAL RESULTS

Experts from academia and industry are interviewed, and the literature is thoroughly reviewed in order to develop the set of criteria and alternative projects. We use the significance of the criteria and DEs in the form of linguistic variables and their corresponding q-ROFNs in Krishankumar et al. [53]. Table I presents the DEs’ weights based on Table I and Eq. (9). Table II presents the importance of DEs to evaluate the alternatives and the assessments of alternatives over a set of criteria.

TABLE I
Weight of DEs

DEs	LVs	q-ROFNs	Score	Rank	Weights
g_1	AI	(0.95, 0.20, 0.240)	0.9456	1.5	0.2577
g_2	VVI	(0.85, 0.30, 0.433)	0.8631	3	0.1983
g_3	VI	(0.80, 0.35, 0.487)	0.8181	4.5	0.1432
g_4	AI	(0.95, 0.20, 0.240)	0.9456	1.5	0.2577
g_5	VI	(0.80, 0.35, 0.487)	0.8181	4.5	0.1432

TABLE II
Linguistic values of alternative by DEs

Criteria	(T_1, T_2, T_3)				
	g_1	g_2	g_3	g_4	g_5
r_1	(VI,VVI,MI)	(A,VI,I)	(VVI,VI,VI)	(VI,I,AI)	(I,U,VI)
r_2	(U,VU,A)	(AU,AU,AU)	(MU,AU,VU)	(AU,VU,U)	(A,AU,MU)
r_3	(VU,AU,A)	(VU,MI,VI)	(U,VU,U)	(A,AU,MU)	(A,AU,U)
r_4	(A,MU,A)	(U,AU,AU)	(A,MU,U)	(MU,A,MU)	(AU,AU,AU)
r_5	(MU,U,MU)	(MI,MI,VU)	(A,MU,MU)	(VI,MU,AI)	(U,U,MU)
r_6	(AU,AU,U)	(I,U,VU)	(AU,U,AU)	(A,MU,AU)	(A,A,AU)
r_7	(VI,VI,I)	(I,I,MU)	(VI,MU,VVI)	(I,VI,AI)	(AI,MI,VVI)
r_8	(MU,U,U)	(MU,U,AU)	(VU,U,VU)	(I,A,VVI)	(AU,VU,U)
r_9	(I,VVI,I)	(VVI,AI,AI)	(MI,VU,U)	(VVI,VI,VI)	(AU,A,VVI)
r_{10}	(VI,AI,VI)	(VI,VVI,AI)	(MI,VVI,VI)	(VVI,VI,AI)	(MU,A,VI)
r_{11}	(I,VI,I)	(AI,VVI,I)	(VVI,VVI,VVI)	(VI,VVI,AI)	(AU,A,VVI)

Table II defines the LDM for each sustainable Public transportation option T_i in Metaverse over diverse factors in the form of LVs. Judgments provided by four DEs have been combined by utilizing the linguistic scale (Krishankuamr et al. [53]) and Eq. (10) into an A-q-ROF-DM $\square = \left(z_{ij}\right)_{m\times n}$, considering the consequence of individual DEs’ opinions and are provided in Table III.

TABLE III
Aggregated q-ROF-decision matrix

Criteria	T_1	T_2	T_3
r_1	(0.760, 0.395, 0.515)	(0.761, 0.400, 0.510)	(0.825, 0.358, 0.438)
r_2	(0.301, 0.801, 0.517)	(0.160, 0.897, 0.412)	(0.351, 0.748, 0.563)

r_3	(0.370, 0.726, 0.579)	(0.310, 0.839, 0.447)	(0.543, 0.598, 0.590)
r_4	(0.406, 0.697, 0.591)	(0.370, 0.747, 0.553)	(0.357, 0.754, 0.552)
r_5	(0.603, 0.551, 0.577)	(0.422, 0.686, 0.593)	(0.711, 0.527, 0.467)
r_6	(0.473, 0.681, 0.559)	(0.337, 0.758, 0.558)	(0.193, 0.874, 0.445)
r_7	(0.806, 0.362, 0.468)	(0.726, 0.433, 0.534)	(0.831, 0.355, 0.428)
r_8	(0.479, 0.671, 0.566)	(0.357, 0.721, 0.594)	(0.560, 0.632, 0.536)
r_9	(0.828, 0.343, 0.444)	(0.817, 0.369, 0.442)	(0.816, 0.318, 0.483)
r_{10}	(0.777, 0.383, 0.500)	(0.859, 0.310, 0.406)	(0.895, 0.271, 0.353)
r_{11}	(0.870, 0.302, 0.390)	(0.811, 0.345, 0.473)	(0.849, 0.325, 0.417)

To find the objective weight, we use the MEREC, given in Eq. (11)-Eq. (15). The resultant values are presented in Fig. 1 and given as

$w_j^M = (0.0822, 0.0541, 0.1034, 0.0888, 0.2026, 0.0777, 0.0817, 0.1286, 0.0657, 0.0576, 0.0576)$.

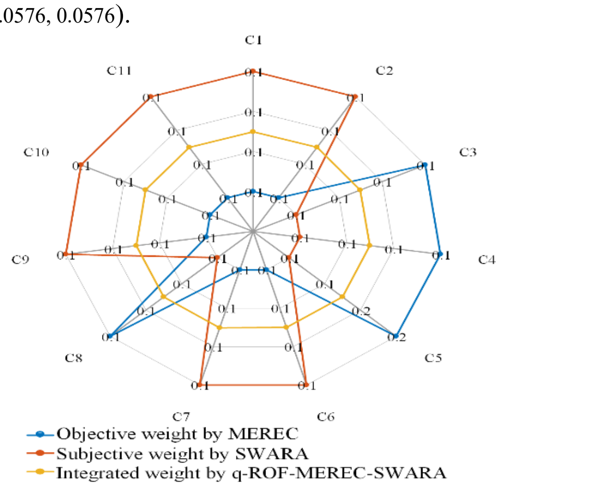

Fig. 1. Weight of criteria using the proposed weighting procedures.

Based on SWARA method (using Eq. (16)-Eq. (18) and Table IV), the resultant values are given in Fig. 1 and presented as follows:

$w_j^S = (0.0971, 0.0957, 0.0913, 0.0713, 0.0873, 0.0863, 0.0972, 0.0856, 0.0938, 0.0952, 0.0993)$.

TABLE IV
Assessment rating of criteria in the form of LTs

C	g_1	g_2	g_3	g_4	g_5	A-q-ROFNs	$S(z_{kj})$
r_1	VH	VH	H	M	AH	(0.788, 0.348, 0.508)	0.814
r_2	VVH	VL	VH	AH	VL	(0.815, 0.394, 0.425)	0.799
r_3	VH	L	VVH	VVH	L	(0.745, 0.427, 0.513)	0.752
r_4	MH	VL	VL	MH	L	(0.476, 0.655, 0.586)	0.485
r_5	H	ML	AL	AH	AL	(0.745, 0.494, 0.448)	0.706
r_6	VH	L	AH	M	VL	(0.708, 0.490, 0.509)	0.695
r_7	VVH	H	L	VH	AH	(0.811, 0.364, 0.457)	0.815
r_8	VH	AL	MH	VVH	VL	(0.697, 0.497, 0.517)	0.686
r_9	MH	AH	M	H	VH	(0.780, 0.406, 0.477)	0.779
r_{10}	VH	VVH	ML	MH	AH	(0.793, 0.389, 0.469)	0.794
r_{11}	H	AH	VVH	H	VVH	(0.832, 0.341, 0.438)	0.836

From the presented q-ROF-MEREC-SWARA procedure, we integrate the q-ROF-MEREC for objective weighting and q-ROF-SWARA weight for subjective weighting by Eq. (19). The integrated weight for $\gamma = 0.5$ is shown in the Fig. 1 and given as follows:

$w_j = (0.0896, 0.0749, 0.0973, 0.0800, 0.1449, 0.0820, 0.0895, 0.1071, 0.0797, 0.0764, 0.0784)$.

According to the Eq. (20)-Eq. (21) and Table III, the linear and vector normalization matrices are estimated for sustainable Public transportation in Metaverse.

From Eq. (22)-Eq. (25), the WSD s_i^d and WSR s_i^r measures with their ranks are obtained. Similarly, using Eq. (26)-Eq. (29), the WPD p_i^d and WPR p_i^r measures with their ranks are obtained. Applying Eq. (30)-Eq. (33), we estimate the modified utility measures for sustainable Public transportation in Metaverse and given in Table V. The overall utility measures (OUM) for sustainable Public transportation in Metaverse is calculated by Eq. (34). From Table V, the alternative denoted as T_2 (Integrating e-car-sharing, e-scooter, e-sharing economy into the Metaverse) is the most appropriate alternative.

TABLE V
The modified utility measures, overall utility measures, and ranking order of alternatives.

Alternatives	u_i^{sd}	u_i^{sr}	u_i^{pd}	u_i^{pr}	u_i	Ranking
T_1	0.964	0.770	0.930	0.941	0.9012	3
T_2	1.000	1.000	1.000	1.000	1.0000	1
T_3	0.977	0.762	0.953	0.957	0.9123	2

A. Sensitivity investigation

When considering a weighting assessment procedure, the utilization of objective and subjective weighting provides a better assessment of the considered criteria. In this line, the criteria weights are obtained by considering only the objective weighting in place of the integrated weighting procedure. Using q-ROF-MEREC, the OUDs and preferences are shown in Fig. 2. The OUDs of alternatives: $T_1 = 0.9017$, $T_2 = 1.0000$, and $T_3 = 0.9069$, and the prioritization order of alternatives are given in the following form $T_2 \succ T_3 \succ T_1$. Applying the q-ROF-SWARA method, the OUDs and preferences are given as follows, The OUDs of alternatives: $T_1 = 0.9013$, $T_2 = 1.0000$ and $T_3 = 0.9191$, and the prioritization order of alternatives is given in the following form $T_2 \succ T_3 \succ T_1$. Hence, it is concluded that using the diverse parameter values will recover the permanence of the q-ROF-MEREC-SWARA-DN-WISP method, which implies the option T_2 (Integrating e-car-sharing, e-scooter, e-sharing economy into the Metaverse) is at the top of the ranking, while the option T_1 (Incorporating the operation of public transport into the Metaverse) has the last rank for each parameter γ values.

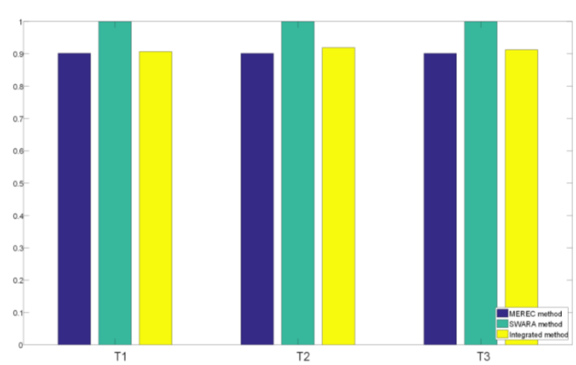

Fig. 2. Sensitivity analysis of utility measures with different weighting procedures.

B. Comparative discussion

In the present section, we compare the developed WISP approach with several MCDM techniques consisting of TOPSIS, VIKOR, COPRAS, WASPAS, MULTIMOORA, and CoCoSo. The comparison results are shown in Fig. 3. From this figure, it can be seen that the most appropriate alternative is T_2 (Integrating e-car-sharing, e-scooter, e-sharing economy into the Metaverse) using almost all MCDM approaches, excluding the TOPSIS (Liu et al. [54]), VIKOR and COPRAS approaches. The other advantages of the proposed q-ROF-MEREC-SWARA-DN-WISP methodology are as follows:

- All the above approaches including the original WISP method [21] use the single normalization process, while the proposed q-ROF-MEREC-SWARA-DN-WISP model uses the double normalization techniques, which avoids the complexity of transforming diverse dimensions under different criteria and the loss of evaluation information.
- In the developed method, the subjective weight of criteria is estimated by the q-ROF-SWARA tool, and the objective weight of criteria is derived by the MEREC process. The presented process can conquer the inaccuracies which rise in an objective or a subjective-weighting model. In contrast, in q-ROF-WASPAS [55], the only objective weight of criteria is estimated with similarity measure-based weighting approach, while in q-ROF-MULTIMOORA [56], only objective weight of criteria is obtained by CRITIC method. In q-ROF-COPRAS [53], the criteria weights are chosen arbitrarily.

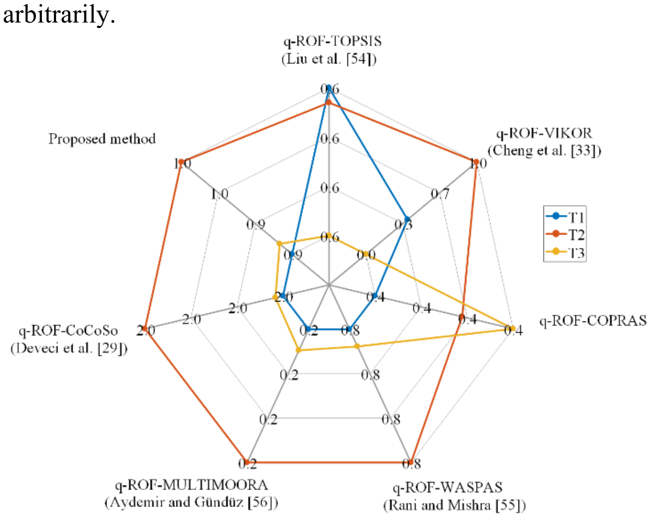

Fig. 3. Variation of various assessment degrees of alternatives with different methods.

- In TOPSIS and VIKOR method, the divergences from an alternative T_i with the q-ROF-ideal solution (IS) and the q-ROF-anti-ideal solution (AIS) are computed for measuring the relative closeness index and compromise solutions of each alternative by means of the given evaluation criteria. The q-ROF-IS and q-ROF-AIS may be considered as standards against which the performance of the alternatives concerning the criteria is evaluated. It can be observed that these standards are not viable to be carried out in reality, while the q-ROF-MEREC-SWARA-DN-WISP method considers the both types of criteria according to the utility degree evaluation, which provides more precise information in comparison with different existing methods mostly considering the benefit or cost criteria. Therefore, the standards are found practicable by using q-ROFGDWA and q-ROFGDWG operators, which is more accurate in the sense that the expert knowledge not only about the IS and AIS performance of alternatives over the criteria but also a relative comparison of the performances among them.

In Fig. 4, it is noticed that the presented method is extremely consistent with extant tools. To maintain uniformity in the technique-related comparison, various appraisal measures and existing methods viz., q-ROF-TOPSIS, q-ROF-VIKOR, q-ROF-COPRAS, q-ROF-WASAPS, q-ROF-MULTIMOORA, and q-ROF-CoCoSo are considered.

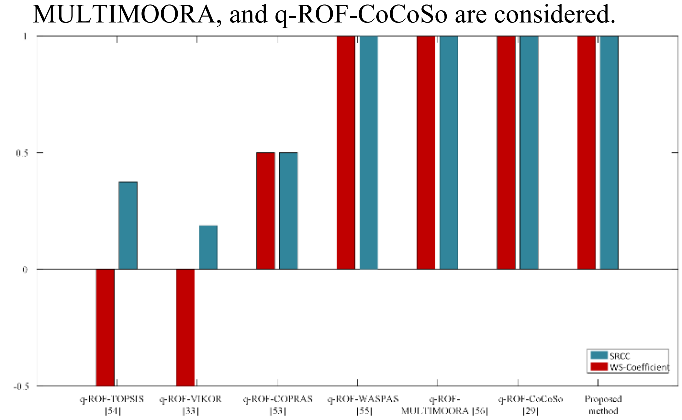

Fig. 4. Correlation and similarity design of ranking orders with different methods.

The "spearman rank correlation coefficients (SRCCs)" and the "WS-coefficients (WSCs)" [57] of priority orders of different extant methods with the proposed q-ROF-MEREC-SWARA-DN-WISP method are shown in Fig. 4. The outcomes of the SRCC and WSC state that it is an appropriate way to associate the similarity of prioritizations, which signifies the homogeneity of prioritization of sustainable Public transportation in the Metaverse is high. Hence, the presented methodology is more reliable and has stability with the formerly introduced models.

VII. DISCUSSION

Incorporating public transport operations into the metaverse (e.g. optimization, demand planning, routing, lines, etc.) was the least sustainable and efficient option. Traffic demand influences both environmental and user considerations in transport. Heavy traffic increases commute times and carbon emissions. Managing traffic demand using sustainable technology can minimize traffic demand and negative impacts on a road network. Promoting innovation and progress in sustainable technology to control transportation demand (e.g. virtual products and experiences) was ranked second.

Micro mobility is a growing transportation sector having policy consequences. Integrating a new application with new technologies is inevitable. Accessible cars will make sharing a more egalitarian transportation option [58]. Integrating e-car-sharing, e-scooter, and e-sharing economy into the metaverse (e.g. supporting sustainable mobility) was deemed the best option.

VIII. Conclusions

The most sustainable and efficient alternative was to integrate e-car-sharing, e-scooter, and e-sharing economy into the metaverse. Transport and IT are linked by constant innovation. Today, transportation and technology are inseparable. Using Metaverse technology with public transportation opens a new research field. Multiple conflicting criteria make evaluating sustainable public transportation a complex MCDM problem. This work develops a q-rung orthopair fuzzy decision-making procedure for assessing and prioritizing sustainable public transportation in Metaverse. For this purpose, an integrated WISP method has been proposed based on the combination of double normalization processes, the generalized Dombi AOs, and the combined weighting model with q-ROFSs. In this method, we made a systematic combination of two normalization procedures and four utility measures to determine the overall utility of alternatives. In this method, the merits and demerits of the two normalization procedures are compensatory. As a result, the information loss caused by the normalization procedure can be reduced. Sensitivity analysis examined different parameter values to show the results' robustness. The results' validity and stability are compared to existing methods.The results show that the proposed approach is important, solid, and consistent with existing methods.Future research can apply the WISP model to water distillation selection, plastic waste management, low carbon supplier selection, and more to verify its efficacy and universality across issue domains. Metaverse technology is new. This technology needs policy implications to prevent harmful outcomes. Existing rules mitigate some of these negative effects in underdeveloped nations, but they may be insufficient when contemplating technology's future. This is a unique study evaluating public transit in the metaverse. This research allows decision-makers to examine how metaverse technology will affect public transportation through alternatives developed under the settings.

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