ORIGINAL ARTICLE

Lane Choice Behavior at Toll Plaza Under Mixed Traffic Conditions Using TODIM Method: A Case Study

Chintaman Santosh Bari[1] · Rohit Chopde[1] · Ashish Dhamaniya[1]

Abstract

The main objective of the present study is to prepare an algorithm for the choice of lane causing minimum delay based on drivers' perception using a Multi-Criteria Decision-Making (MCDM) method. The TODIM (Portuguese acronym for Interactive Multi-Criteria Decision-Making) is based on the prospect theory. The effect of human behavior on lane choice at toll plaza is studied using the user perception survey. The data required is collected by pictorial survey at the toll plaza, nearby petrol pumps, and hotels. The pictorial survey includes the scenarios to understand the lane choice based on the user preferences about the vehicle composition, number of vehicles in queue, and lane changes. In the case of toll plazas, toll lanes are the alternatives, and vehicle composition of toll lanes, number of vehicles in the queue, and number of lane changes required to choose the target lane are all different criteria. A vehicle entering the toll area has to take care of all the available conditions and select an alternative to minimize the delay. The TODIM method requires the weightage matrix of the criteria, which is obtained using the Analytical Hierarchical Process (AHP). It is seen that the number of vehicles in the queue has the highest weightage followed by the proportion of heavy vehicles. These are the prime factors affecting the lane choice behavior at the toll plaza. The algorithm can be further used to predict the best alternative for the emerging vehicle, which will help to minimize its delay.

Keywords Lane choice · Prospect theory · TODIM method · Analytical Hierarchical Process

Introduction

In developing countries like India, road infrastructural projects are taken up under a public–private partnership (PPP) basis. Also, vehicles are growing at a rapid rate, and hence, users still face delays at toll plazas over National Highways (NHs) and State Highways (SHs). To curtail the congestion levels at toll plazas, the Government of India (GOI) has started implementing a full Electronic Toll Collection (ETC) system, commonly called FASTag. However, the congestion is still observed to significant degrees, as shown in Fig. 1. It is observed that, despite the presence of dedicated lanes for each vehicle class at toll plazas, the heterogeneity in driving behavior results in vehicles occupying any desirable lane causing mixed traffic conditions (presence of different leader–follower pair in a toll lane) at toll plazas (Fig. 1).

These mixed traffic conditions cause variation in the service time [1–3], and hence, the delay is experienced by the users, and extra emissions are also observed [4].

For operational performance, detailed knowledge concerning queueing aspects needs to be developed due to demand at a toll plaza. Dubedi et al. [5] stated that the most significant factors affecting the queuing process at a toll plaza depend upon the arriving volume and approaching driver's toll lane choice behavior. The main determinant of lane choice is to minimize the delay at the toll plaza. Furthermore, at toll plazas, the choice of lane also involves risk to the drivers in terms of extra delay on choosing the wrong lane. Hence, it is essential to choose the correct lane at toll plazas. As of now, the technology worldwide is moving toward the autonomous vehicles environment that requires programming for different scenarios at different facilities like toll plazas, etc., to make the decisions while plying on the road. Moreover, the use of simulators has increased in the recent past to study microscopic traffic behavior and safety analysis. It can be noted that about 33% of crashes happen while lane changes. Thus, there is a need to replicate

✉ Ashish Dhamaniya
  adhamaniya@gmail.com

1 Sardar Vallabhbhai National Institute of Technology, Surat, India

Fig. 1 Mixed traffic condition at the toll plaza

the real-world field scenario in the simulator using some specified models, including the car-following and lane-changing models. The car-following model can handle the kinematic parts for longitudinal motions, and for lane-changing decisions, lane change models are supposed to handle in the simulator [6]. Different methods, such as discrete choice models [5, 7], the concept of shortest lanes [8–10], and rod speed [11], were described in the past studies for lane choice behavior at toll plazas. Considering the shortest lane concept, it is often observed that the drivers observe the simultaneously many shortest lanes while approaching toll plazas, but then, the other factors such as traffic composition in lanes and lane changes required, etc., may affect his decision to choose. Therefore, the users' perception is also important to know the preferences for different lanes (i.e., alternatives) with respect to different criteria (number of vehicles in the queue, lane changes required, etc.) observed in the field. Most of the studies have considered only two vehicle classes, and as per authors' knowledge, limited studies are available on the lane choice studies at toll plazas for mixed traffic conditions (presence of different vehicle classes in a single lane). Hence, the main aim of the present study is to develop a model for lane choice at toll plazas operating under mixed traffic conditions.

The methodology of discrete choice theory (DCT) is a separate field in scientific literature and is almost never mentioned next to the Multi-Criteria Decision-Making (MCDM) methods in the scientific literature [12, 13]. The DCT is a decompositional method used for finding weights in the literature (obtaining combined weights using the decision-maker's (DMs) preferences for whole alternatives) [14]. The DCT depends upon the expected utility theory [15]. The basic assumption of this theory is that the DM can choose the alternative with the maximum utility value (i.e., rational behavior of the DM [16]). Furthermore, the assumptions are (a) consistency for preference for alternatives, (b) linearity in assigning decision weights to alternative, and (c) reference independent choice of alternative. The assumption of the DCT as the DM are rational is always not true, as, in real-world conditions, the DM can be affected by their cognitions

[17]. Furthermore, DMs may have bias while dealing with the conditions of having risk (gains and losses) and uncertainties [18]. Additionally, most DMs have problems when dealing with many criteria and alternatives at a time, and for dealing with this situation, the literature suggests the use of MCDM methods [19]. Hence, due to the shortfall of the DCT, the MCDM approach is used in the present study. MCDM is defined as "an extension of decision theory that covers any decision with multiple objectives" by [20]. It presents a systematic process of solving the problem in case of multiple criteria [21]. In case of more number of conflicting criteria, it helps people for making decisions according to their preferences [22]. Depending upon the nature of the problem, MCDM combines the criteria into a single value for final results [23]. The main aim of the MCDM is to (a) categorize the group of alternatives among the given set of alternatives, (b) rank the alternatives based on their performance, and (c) select the optimum/best alternative [23, 24]. MCDM can handle problems related to risks, uncertainties, long-term time horizons, and complex value issues [25]. The basic methodology of any MCDM initiates with the decision matrix of $n \times m$, where n is the number of criteria and m is the number of alternatives. Based on the nature of the alternatives that are to be evaluated, i.e., either ranking, selecting best optimal, etc., MCDM bifurcates majorly into two different groups as continuous and discrete methods [26]. Continuous methods, such as linear programming, goal programming, etc., are more focused toward the identification of the optimal solution/quantity, which can vary infinitely in a decision problem. Discrete MCDM methods include methods of utility or value function and outranking methods. In discrete methods, the alternatives are discrete and are expressed by the number of criteria. As discussed earlier, the lane choice at toll plazas depends upon the number of factors (criteria) and the number of lanes is alternative for the lane choice, which is totally an MCDM problem. Several MCDM methods are available for solving the problem depending upon its need and the importance of the problem. According to the problem, various researchers tried to set a framework for choosing the best MCDM method [26–28]. Various MCDM methods are available, and when to use which method is difficult to answer.

Considering the problem for lane choice, choosing all the DMs (here drivers) as a rational will lead to error as there is risk and uncertainty depending upon the traffic and surrounding conditions. The risk in terms of extra delay by choosing the wrong lane and uncertainty in the guessing and judging the traffic conditions (mostly queued vehicles) happens while approaching a toll plaza. Different MCDM methods, such as the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE), etc., are available, but they

did not consider the physiological effect of the DMs. To deal with such conditions, the literature suggests the use of the TODIM method.

TODIM (Portuguese acronym for Interactive Multi-Criteria Decision-Making) is an interactive (defined as "a progressive evolution and definition of DM preferences through an interaction between him and the results generated from various runs of the model" [29, 30]) MCDM method based on the prospect (here prospect means a list of occurrences and probabilities [31]) theory formulated by Gomes and Lima [32]. Prospect theory is a psychology theory that describes how people make decisions when presented with alternatives that involve risk, probability, and uncertainty [33]. Kahneman and Tversky [34] introduced the prospect theory as a descriptive-behavioral theory; it tries to describe how individuals make choices in real life rather than how they should do it to optimize some 'objective' interests. This theory overcomes the two paradoxes caused due to the DCT: (a) Alliax Paradox (users overweight some effects [35]) and (b) Framing effect (perseverance of different utility by the users depending upon the gain and loss [34]) (for more details and example, please see [31]). To deal with these paradoxes, prospect theory uses the value function to mimic the users' perception under gain/loss conditions.

Prospect theory can be explained better using the graph (Fig. 2) in terms of monetary loss. Therefore, according to prospect theory, the sorrow of losing $1000 is more than the joy of gaining $1000. People are always afraid of losing things rather than being confident of gaining. To nullify the effect of losing $1000, one may have to gain $2000. The same can be applied to the delay caused at the toll plaza. The happiness of a person experiencing less delay at toll will be less than the sorrow of the same person experiencing more delay at the toll plaza.
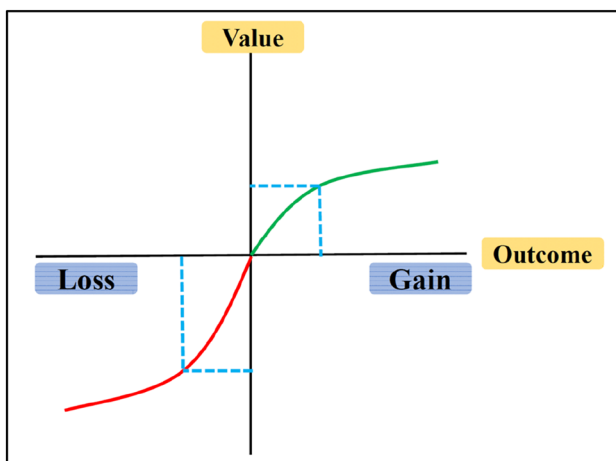

Fig. 2 Value function of the TODIM method

Literature Review

As the present study deals with the lane choice study at toll plazas, literature related to the different approaches used by the researchers is discussed here.

Dubedi et al. [36] used a random utility-based discrete multinomial choice model to represent car lane choice behavior at the Manual Toll Collection (MTC) system. The number of heavy vehicles in the queue and the number of lane changes required were considered major factors for toll lane choice. Lin and Su [37] stated that the gate choice depends on the equivalent queue length of the toll lane, which includes the actual queue length of the toll lane plus the lane changes to be done. Gulewicz and Danko [10] found that the drivers prefer to choose the toll lane with the shortest queue length, requiring minimum lane changes. Mudigonda et al. [8] proposed lane selection based on complex inter-vehicle dynamics. They proposed a utility-based heuristic model for each toll lane. According to the authors, the vehicle chooses the lane with the highest utility. Hill et al. [38] showed that lane-changing is affected by the degree of congestion, drive type, and location-specific factors. The lane change duration was greater in congested conditions than in uncongested states. Chakroborty et al. [7] showed that the arrival process to a queue is dependent on the state of all queues. The queueing at the toll plaza was modeled as a multiple-queue queuing system. They proposed a model to determine the steady-state probability density function. Yu and Mwaba [11] showed a lane choice model for autonomous vehicles based on two parameters, the rod speed SR_i and the decision-making parameter D_{SRi}. Higher the value of both the parameters, more favorable the lane to choose. TODIM method was first used to evaluate the road improvement alternatives in Brazil by Gomes and Lima [32]. It can handle qualitative and quantitative datasets and also can deal with heterogeneous information at a time [39]. The TODIM method is used in various applications, such as rental evaluation of the residential buildings [40], selecting the best option for transportation of natural gas [41], evaluation of broadband Internet plans [42], etc. Gomes et al. [43] proposed the new model as extended TODIM using Choquet integral, based on non-linear cumulative prospect theory. In the extended TODIM method, the measure of dominance was altered with the help of the Choquet integral. The results showed that the extended TODIM has some advantages over than traditional TODIM method. The limitation of traditional TODIM is that it only considers the real numbers. However, this limitation is also overcome by hybrid and extended TODIM methods using fuzzy numbers [44–47]. Farooq et al. [48] evaluated different factors affecting the lane change using the MCDM approach as

Analytical Hierarchical Process (AHP) and Best Worst Method (BWM). They found that traffic characteristics significantly affect lane changes (obtained highest weightage among all criteria). Sun et al. [49] used the prospect theory for travel choice for the car drivers in the return trip. Li et al. [6] applied the MCDM method for the lane change model. The proposed method was flexible and provided better results than the artificial intelligence-based methods. Long et al. [50] used the cumulative prospect theory for the study of lane-changing behavior. They concluded that the cumulative prospect theory predicts lane changes better due to the presence of risk aversion factor.

Thus, it can be seen from the literature mentioned above review that lane choice behavior is studied by various approaches and at different facilities. With this basic knowledge from literature, the objective of the present study is framed as stated in the section below.

Research Objective

The queuing process at the toll plaza is an important aspect for designing it, which depends on the toll lane choice behavior of the drivers approaching the toll plaza. In the case of toll plazas, toll lanes are the alternatives, and vehicle composition of toll lanes, number of vehicles in the queue, and number of lane changes required to choose the target lane from the approach lane are all different criteria. A vehicle entering the toll area has to take care of all the available conditions and select an alternative to minimize its own delay. As observed from the literature, limited studies are available for lane choice study at toll plazas operating under mixed traffic conditions (presence of different vehicle classes in the dedicated lane); the present study aims to develop an algorithm for lane choice at toll plazas. Furthermore, the drivers' physiological behavior is also not considered in the literature. Therefore, after critical review and considering the risk and uncertainty associated with the lane choice, the TODIM method is found to be well suited for the present study. The present study thus assessed the weights for different criteria with the help of AHP and then calibrated the value of the loss aversion factor (Θ) depending upon the pictorial survey.

Data Acquisition for Model Development

The effect of human behavior on lane choice at toll plazas is studied using the user perception survey. A drone survey was carried out at the Kamrej Toll Plaza located on National Highway (NH-48) near Surat. The toll plaza is on the busiest route that joins the capital of the country (i.e., New Delhi) and the economic capital of the country (Mumbai). Heavy traffic is observed on this route, and hence, it is selected as a candidate toll plaza for data collection. The video graphic data were then used to frame the scenarios for the pictorial survey (survey including the field photographs to choose one of the given alternatives, here toll lane) corresponding to the field conditions based on the factors that affect the lane choice behavior. The required lane choice selection data are collected by pictorial survey at the toll plaza, petrol pumps, and hotels nearby to the toll plaza. The pictorial survey includes the scenarios formed at the toll plaza to understand user preferences about the vehicle composition, number of vehicles in the queue, and number of lane changes which will be used to form a lane choice algorithm. Data were collected only for car drivers, as it has a maximum share of 65 percent in the traffic stream as observed during the videographic survey, and at the same time, the perceived delay of car users is significant as far as the monetary loss is concerned [51]. Also, informing the car user about the choice of the lane and adapting the technology of lane choice prediction in the car are easy as compared to the heavy vehicle drivers due to differences in education level. About 450 car drivers were surveyed through the pictorial survey. The survey was carried out in normal weather conditions after the first lockdown by taking precautions for COVID-19.

The sample question of the pictorial survey that has been asked to the car drivers is shown in Fig. 3.

Criteria and Alternatives

The analysis is done using the TODIM method by forming a performance matrix between different alternatives and criteria observed from the field condition.

Different criteria considered in the study are as follows:

- Number of Vehicles in the Queue (QL):

When a vehicle enters the toll area and decides to choose a toll lane, the total number of vehicles in each lane is taken as the first criteria to define alternatives. For example, the QL in toll lane 1 is 7 (Fig. 3).

- Number of Lane Changes Required (LC):

When a vehicle enters the diverging area from the approach lane, the total number of lane changes he/she has to make from the approach lane to the targeted toll lane is the lane change for the alternative. For example, if the subject vehicle shown in Fig. 3 wants to choose toll lane 3, then the total number of LC he needs to make is 2.

- Proportion of Heavy Vehicles (P(HCV)):

Fig. 3 Sample question for the pictorial survey

It is the ratio of the number of heavy vehicles to the total number of vehicles in each alternative. For example, the P(HCV) in alternative 4 is 50% (Fig. 3).

- Proportion of Trailers (P(Trailer)):

It is the ratio of the number of trailers to the total number of vehicles in each alternative. For example, the P(Trailer) in alternative 4 is 25% (Fig. 3).

In the present study, the toll lanes are the alternatives. As shown in Fig. 3, all the toll lanes have some queued vehicles, with P(HCV) and P(Trailer), while the subject vehicle shown has to change lanes to choose a toll lane other than toll lane 1. Thus, all the toll lanes are alternatives.

TODIM: A Pedagogical Explanation

As discussed earlier, the TODIM is based on the prospect theory and was developed by Gomes and Lima [32]. The prospect theory is a mixture of behavioral economics and risk. In the original research formulation, the prospect was named after the lottery system as it includes the risk of gain and loss. A prospect $(x_1, p_1; \ldots; x_n, p_n)$ is a contract that yields outcome x_i with probability p_i, where $p_1 + \cdots + p_n = 1$. The base of prospect theory is (a) reference dependence, (b) probability weighting, and (c) loss aversion. As DMs, attitudes are always not rational, and hence, they may choose differently when there is a gain or loss in an event. To deal with this, the value function is developed in the prospect theory, which is reference-dependent. For a reference point, the value function is zero. Here, gains are the outcomes that are obtained more than the reference point, and losses are lower than it. The value function thus is reference-dependent (X-axis in Fig. 2), which divides the gains (upper part in

value function) and losses (lower part in value function). The shape of value function is developed by [34] using the principle of diminishing sensitivity (effect if more for smaller gain/loss than for larger gain/loss), and hence, the concave curve is used for gain, and the convex curve is used for losses (Fig. 2). The second base is the use of the non-linearly increasing probability weighting function instead of probability. It allows to underweight the large probabilities and over weighting of small probabilities. The third and the last one is the loss aversion. Unlike random utility theory, four separate patterns of risk attitudes are present due to value function. Loss aversion is generally giving more priority to the losses than the gains, in other words, more sensitivity to gains. Literature shows that the DMs show risk-averse behavior for gains and risk-seeking for losses [34] (For further reading, see [52–54]).

First, the decision matrix is to be found out. The decision matrix is obtained from the values from the pictorial survey. As all the values are in different units, the normalization is carried out to bring the values in the same unit, which lies between 0 and 1. For example, the number of vehicles in the queue ranges from 0 to n, while the P(HCV) and P(Trailers) lie between 0 and 1. Hence, the normalization is carried as given in step 2 of Fig. 4. The TODIM method required the selection of the reference criterion for the calculations, and hence, in the present study, the highest valued criterion is taken as the reference criterion.

In the TODIM method, the shape of the value function is the same as the gain–loss function of prospect theory. It uses a global measurement value. The value function shows the 'S-shaped' growth function, which reflects the behavior of DM with respect to gains and losses. Thus, the reference dependence value function is incorporated in the TODIM (see step 3 of Fig. 4, the first equation is for gain as the difference is more than 0, second shows no loss no

Fig. 4 Algorithm for TODIM
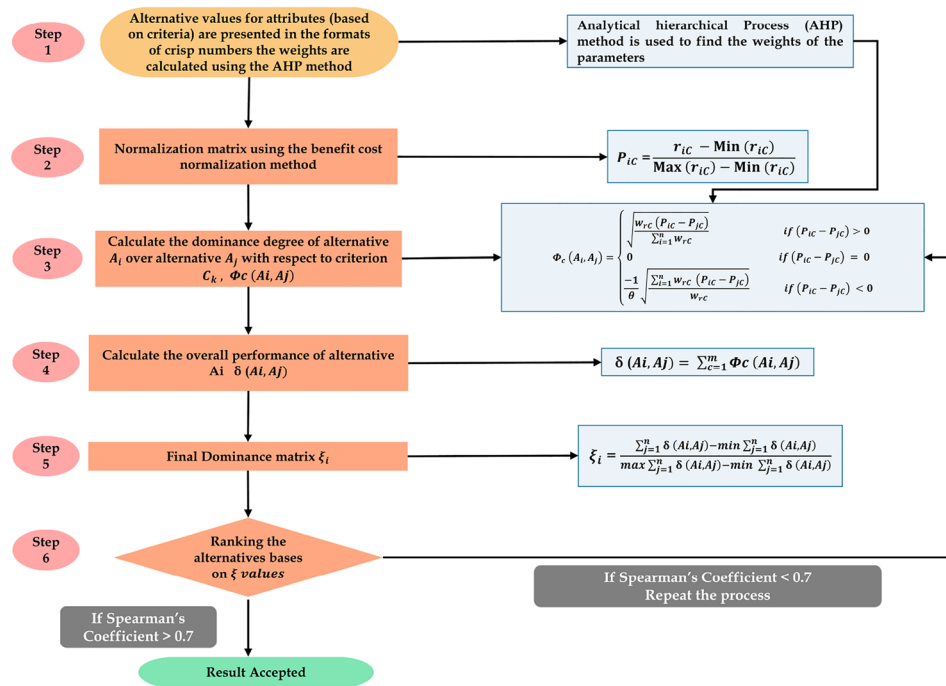
gain, as difference $= 0$, and the third formula shows the loss, as the difference is less than 0). If the value of $(P_{ic} - P_{jc})$ is greater than 0, then it is gain (upper portion of the horizontal axis representing concave curve in Fig. 2), and if the value comes out to be negative, then it represents the loss (lower portion of the horizontal axis representing convex curve in Fig. 2). The value of 0 represents the condition of no loss and no gain. The second base of prospect theory, i.e., probability weighting, is incorporated using the ratio of relative weight to the summation of the relative weights ($w_{rc}/\sum_{i=1}^{n} w_{rc}$). The last base, i.e., the loss aversion, is added as the loss aversion factor (θ) (see step 3 of Fig. 4, given for difference less than zero) in the TODIM method called as attenuation factor. Different values of θ obtain different shapes of the prospect value function in the losses, i.e., the convex part of the value function. Afterward, the summation of all gains and losses leads to the final measurement of each alternative Ai over each alternative Aj [41] (see step 4 of Fig. 4). Finally, the final matrix of dominance or the global value of each alternative is found out using the normalization of the corresponding dominance values (see step 5 of Fig. 4). Finally, the alternative with the global value is ranked first among all (for more details, please refer, [41, 43]). In the present study, the value of θ is tuned to match the ranking obtained by the user's perception. The observed and predicted ranks of the alternative are compared using Spearman's rank correlation coefficient (ρ). The value of θ is fixed when the ρ is maximum.

The TODIM method requires the weightage matrix of the criteria, which is obtained in the present study using the Analytical Hierarchical Process (AHP) process. The Analytical Hierarchical Process (AHP) is a better way of finding the weights of the factors using the pairwise comparison matrix filled by the decision-maker [55–57]. AHP was founded by Saaty, in which the intangible factors are measured on a scale to make them tangible [57] as the relation between two factors is judged by the experts and is then scaled to formulate the weights. AHP is used in the decision-making in the field of personal decision-making, social selection, and engineering selection, and also in the evaluation and selection. Holguín-Veras [58] compared the AHP and multi-attribute value (MAV) functions for highway planning. The author concluded that AHP is better than the MAV method in terms of hierarchy. He et al. [59] developed the evaluation index with safety, economic, technical, and time factors for highway projects using AHP and Grey Correlation Analysis. Taherdoost [60] suggested that AHP is a step-by-step approach that also works on a mixture of qualitative and quantitative attributes. Lidinska and Jablonsky [61] addressed AHP as a structuring and analysis tool for complicated decision-making problems and is ideal for such tasks.

Thus, the AHP is a threefold system with goals/objectives at the top, followed by attributes, and finally, the alternatives. It deals with the decision-making of both the qualitative and quantitative factors. AHP uses the user input to find the weights. The methodology for computing weights through AHP includes:

1. Identify the goals, criteria, and sub-criteria.
2. Then the relative importance matrix (Eq. 1) is found out by inquiring the experts/decision-makers (DM) (here experienced drivers) having experience in that field using the scale given in Table 1

$$A_{M \times M} = E_1 \ E_2 \ E_3 \ \dots \ E_M$$

$$
\begin{array}{c}
E_1 \\
E_2 \\
E_3 \\
\vdots \\
E_M
\end{array}
\begin{bmatrix}
1 & e_{12} & e_{13} & \dots & e_{1M} \\
e_{21} & 1 & e_{23} & \dots & e_{2M} \\
e_{31} & e_{32} & 1 & \dots & e_{3M} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
e_{M1} & e_{M2} & e_{M3} & \dots & 1
\end{bmatrix},
\tag{1}
$$

$A_{M \times M}$ is the relative importance matrix (say A_1); M is the number of attributes.

The importance for each pair of factors is recorded in the respective box, say a_{ij}. Now, for vice versa $a_{ji} = 1/a_{ij}$. For $i = j$ $a_{ij} = a_{ji}$. For example: if, according to the experts, the number of vehicles in the queue is extremely important than the number of lane changes, then in the matric $a_{ij} = 9$, at the same time $a_{ji} = 1/9$.

3. The relative normalized weight (wj) of each attribute is found out by taking the geometric mean (GM), as shown in Eq. (3)

$$GM_j = \left[\prod_{j=1}^{m} a_{ij} \right]^{1/M} \tag{2}$$

$$w_j = \frac{GM_j}{\sum_{j=1}^{m} GM_j}. \tag{3}$$

The weighted matrix is taken as A_2

$$A_2 = [w_1, w_2, w_3, \dots w_M]. \tag{4}$$

Now, the matrices A_3 and A_4 are calculated using Eqs. (5) and (6), respectively

$$A_3 = A_1 \times A_2 \tag{5}$$

$$A_4 = \frac{A_3}{A_2}. \tag{6}$$

The maximum eigenvalue (λ_{max}) is calculated by taking the average of matrix A_4.

Consistency index CI is calculated using Eq. (7)

$$CI = \frac{(\lambda_{max} - M)}{(M - 1)}. \tag{7}$$

The consistency ratio is used to check the consistency of the pairwise comparison matrix given by a particular individual and is calculated as per Eq. (8)

$$CR = \frac{CI}{RI}, \tag{8}$$

where RI is the Random index which is given by Saaty [57]. The value of CR should be less than 0.1, and then, only the weights are said to be consistent. If not, then a combined matrix is to be formed, as suggested by Wakchaure and Jha [55].

If CR is more than 0.1, then the combined matrix is to be developed. The procedure of finding the combined matrix suggested by Wakchaure and Jha [55] is adopted in the present study. Suppose the values given by 'n' respondents for a_{12} are $x_1, x_2, \dots, x_n$, and priority weights given by 'n' respondents are $w_1, w_2, \dots w_n$, where the priority weight is obtained by subtracting the consistency ratio from 1, then for the combined matrix, the value of a_{12} is calculated using Eq. (9). Similarly, for other factors, the final weights are calculated

Table 1 Scale for AHP (Source: [62])

Intensity of importance	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective
3	Moderate importance	Experience and judgments slightly favor one activity over another
5	Strong importance	Experience and judgments strongly favor one activity over another
7	Very strong	An activity is favored very strongly over another, its dominance demonstrated in practice
9	Extreme importance	Evidence favoring one activity over another is of the highest possible order of affirmation
Reciprocals of above	If activity i has one of the above non-zero numbers assigned to it when compared to activity j	
1.1–1.9	If the activities are very close	Difficult to assign the best value, but when compared with other contrasting activities, the size of the small numbers will not be too noticeable

Table 2 Sample matrix of relative importance

Number of attributes = 4	QL	LC	P(HCV)	P(Trailer)
QL	1	9	5	5
LC	0.11	1	0.20	0.20
P(HCV)	0.20	5	1	7
P(Trailer)	0.20	5	0.14	1

QL is the (Queue length) number of vehicles in queue, *LC* is the number of lane changes, *P(HCV)* is the proportion of HCV in the queue, *P(Trailer)* is the proportion of trailer in the queue.

$$a_{12} = \left[x_1^{w_1} * x_2^{w_2} * \cdots x_n^{w_n} \right]^{\frac{1}{[w_1+w_2\ldots+w_n]}}. \tag{9}$$

The steps from (1)–(7) are carried out on the combined matrix, and thus, the final weights are obtained, which can cumulate the users' perception of different decision-makers.

After obtaining the weights by the AHP method, the TODIM method is adopted to get the rank of alternatives. Figure 4 shows the step-by-step approach for solving the decision matrix using TODIM.

Data Analysis

As described earlier, the TODIM method required weights of the different criteria, and hence, AHP method is discussed first for obtaining weights.

AHP Method for Defining Weights

Step 1: The matrix of relative importance is obtained by inquiring the experts or decision-makers. As the study is for lane choice behavior, the DMs are the drivers having experience of driving through the toll road. About 25 experienced drivers were taken to find the weights using the AHP method. The relative importance was recorded on a scale shown in Table 1. For example: if, according to the experts, the number of vehicles in the queue is extremely important than the number of lane changes, then in the matric $a_{ij} = 9$, at the same time $a_{ji} = 1/9$. The matrix showing the relative importance is shown in Table 2. This is matrix A_1.

Step 2: Matrix A_2 is calculated using the Eq. 2 using Table 2

$$GM_{(QL)}[1 \times 4.04 \times 1.37 \times 1.11]^{\frac{1}{4}} = 3.873.$$

Step 3: Similarly, the geometric mean for other attributes is also calculated, and their summation is done. Now, the weight is founded using Eq. 3

$$w_i = \frac{3.873}{\sum_{j=1}^{m} GMj} = \frac{3.873}{6.373} = 0.61.$$

Hence, using Eq. 4

$$A_2 = [0.61, 0.04, 0.26, 0.10].$$

Step 4: The matrix A_2 obtained from Eq. 4 is the weightage matrix. The summation of weights of all the attributes should be equal to one, i.e., $\sum_{j=1}^{m} w_j = 1$. Also, the consistency of the weights obtained is to be checked. To check the consistency, matrix A3 and A4 are estimated using Eqs. 5 and 6, respectively.

$$A_3 = A_1 \times A_2$$

$$\begin{bmatrix} 1 & 9 & 5 & 5 \\ 0.11 & 1 & 0.20 & 0.20 \\ 0.20 & 5 & 1 & 7 \\ .20 & 5 & 0.14 & 1 \end{bmatrix} * [0.61, 0.04, 0.26, 0.10].$$

$$A_3 = [2.73, 0.18, 1.25, 0.46].$$

$$A_4 = \frac{[2.73, 0.18, 1.25, 0.46]}{[0.61, 0.04, 0.26, 0.10]} = [4.49, 4.40, 4.92, 4.74].$$

Step 5: The maximum eigenvalue (λ_{max}) is calculated by taking the average of matrix A_4.

$$\lambda_{max} = \frac{4.49 + 4.40 + 4.92 + 4.74}{4} = 4.64.$$

Step 6: Consistency index (CI) is calculated using Eq. 7

$$CI = \frac{(4.64 - 4)}{(4 - 1)} = 0.21.$$

Step 7: Consistency ratio (CR) is calculated with Eq. 8

$$CR = \frac{CI}{RI} = \frac{0.21}{0.89} = 0.24,$$

where RI is the Random index which is given by [55] is equal to 0.89 in the present case. The value of CR is greater than 0.1; hence, the weights obtained are inconsistent. Now, the consistent weights are obtained using Eq. 9. For the combined matrix, the priority weights of all the respondents are determined and the new cell value of a_{ij}, using Eq. 9. The consistent weights with CI = 0.03 and CR = 0.02 which is < 0.1 for combined matrix are shown in Table 3.

From Table 3, it is clearly seen that the highest weight of 0.36 is allocated to queue length, followed by the proportion of heavy vehicles with weight 0.31, proportion of trailer with weight 0.23, and lowest is assigned to lane

Table 3 Combined matrix for AHP with weights

	QL	LC	P(HCV)	P(Trailer)	GM	A$_2$ (Weights)	A$_3$	A$_4$
QL	1	4.04	1.37	1.11	1.573	0.36	1.46	4.09
LC	0.25	1	0.43	0.47	0.471	0.10	0.43	4.04
P(HCV)	0.73	2.35	1	1.92	1.347	0.31	1.26	4.10
P(Trailer)	0.90	2.13	0.52	1	1.001	0.23	0.94	4.12
				$\sum GM =$	4.393	1.00	λ_{max}	4.09
							CI	0.03
							CR	0.03

Table 4 Decision matrix (performance value of each alternative for respective criteria)

Alternative	Criteria			
	Number of the vehicle in the queue	Lane changes	Proportion of heavy vehicle	Proportion of trailers
Lane 1	7.00	0.00	0.00	0.00
Lane 2	4.00	1.00	1.00	0.00
Lane 3	6.00	2.00	1.00	0.00
Lane 4	4.00	3.00	0.50	0.25
Lane 5	3.00	4.00	0.67	0.00
Lane 6	3.00	5.00	0.67	0.00
Lane 7	2.00	6.00	0.00	0.00

Table 5 Normalized matrix

Alternative	Criteria			
	Number of vehicle in queue	Lane changes	Proportion of heavy vehicle	Proportion of trailers
Lane 1	1.00	0.00	0.00	0.00
Lane 2	0.40	0.17	1.00	0.00
Lane 3	0.80	0.33	1.00	0.00
Lane 4	0.40	0.50	0.50	1.00
Lane 5	0.20	0.67	0.67	0.00
Lane 6	0.20	0.83	0.67	0.00
Lane 7	0.00	1.00	0.00	0.00

Table 6 Criteria weights

Criteria	Base weights	Relative weights
Number of vehicle in queue	0.36	1
Lane Changes	0.11	0.30
Proportion of Heavy vehicle	0.31	0.86
Proportion of Trailers	0.23	0.64

changes having a weightage 0.1. This shows that the people prefer to choose the toll lane with the shortest queue mostly. Lane change being the last shows that it is given the least priority. Queue length is the factor that affects the people most in selecting the toll lane.

TODIM Method

In this analysis, a sample example for one scenario is presented.

Step 1: A decision matrix is generated by observing the values given in scenarios of the pictorial survey, which contains performance values of each alternative for each criterion. As shown in Fig. 3, different lanes are alternatives given as rows in Table 4, and different criteria are given as columns. Here, the vehicle is approaching in the lane, and according to it, the lane changes are given in Table 4.

Step 2: Decision matrix is normalized by linear normalization method using Eq. (10), where $P_{ik} = \{0, 1\}$. Normalization is performed to remove the effect of the different scales used in various criteria [63]. Table 5 shows the normalized matrix for all criteria

$$P_{iC}^* = \frac{r_{iC} - \min(r_{iC})}{\max(r_{iC}) - \min(r_{iC})}. \qquad (10)$$

Step 3: The weight of each criterion is decided by the decision-maker on a numerical scale and is then normalized. Thus, the relative weight w_{rC} is the weight of criterion C divided by the weight of the reference criterion 'r', where the reference criterion is the one with the highest weight. The base weights in Table 6 are obtained by the AHP methodology as explained above. As observed from Table 6, the number of vehicles in the queue has the highest weightage than all other factors, i.e., the approaching driver is giving priority to the shortest queue. Though, in some times, it is affected by the lane changes required but with last priority.

Step 4: Partial matrix of dominance is calculated using Eq. (11)

$$\Phi_c\left(A_i, A_j\right) = \begin{cases} \sqrt{\dfrac{w_{rc}\left(P_{iC}-P_{jC}\right)}{\sum_{i=1}^{n} w_{rc}}} & \text{if } \left(P_{iC}-P_{jC}\right) > 0 \\ \quad\quad 0 & \text{if } \left(P_{iC}-P_{jC}\right) = 0 \\ \dfrac{-1}{\theta}\sqrt{\dfrac{\sum_{i=1}^{n} w_{rc}\left(P_{iC}-P_{jC}\right)}{w_{rc}}} & \text{if } \left(P_{iC}-P_{jC}\right) < 0 \end{cases}$$

(11)

$$\delta\left(A_i, A_j\right) = \sum_{c=1}^{m} \Phi_c\left(A_i, A_j\right) \; i, j = 1, 2, \dots n. \quad (12)$$

$\delta(A_i, A_j)$ represents the measurement of the dominance of alternative A_i over alternative A_j. Thus, all alternatives are compared with each other for each criterion. θ is constant and is always greater than 0. The value of θ determines the effect of the losses (i.e., when $P_{ik} < P_{jk}$): If $\theta > 1$, the losses are attenuated, while if $\theta < 1$, the losses are amplified [64]. It is necessary to consider the psychological behavior of decision-makers when dealing with MCDM problems [65]. The TODIM is based on the prospect theory and was developed by Gomes and Lima [32]. In the traditional TODIM method, it has been stated that the θ is always positive based on prospect theory. However, the positive value of θ denotes the attitudes of the drivers as risk-seeking or risk aversion. Here, when the θ is smaller than one, it means the driver is more cautious, and he/she tries to avoid the lane changes and may join the lane visible in front. Higher the value of θ means the driver is showing less cautious behavior, and he/she tried to accelerate and change the lanes due to the provision of a flare zone in front of it while approaching the toll lanes. Generally, it is recommended to use the value of θ as unity, but the psychological behavior of people varies from person to person. Thus, it is necessary to find the optimum value of θ to grasp the psychological behavior of drivers.

To find the value of θ, sensitivity analysis is carried out for different values of θ from 1 to 9, and the value of Spearman's coefficient (ρ) is checked for each value of θ. Here, the variation of θ is considered from 1 to 9 with an interval of one as for the lane choice; the delay should be minimum (losses should be attenuated). By increasing the value of θ, mathematically, the slope of the negative part of the value
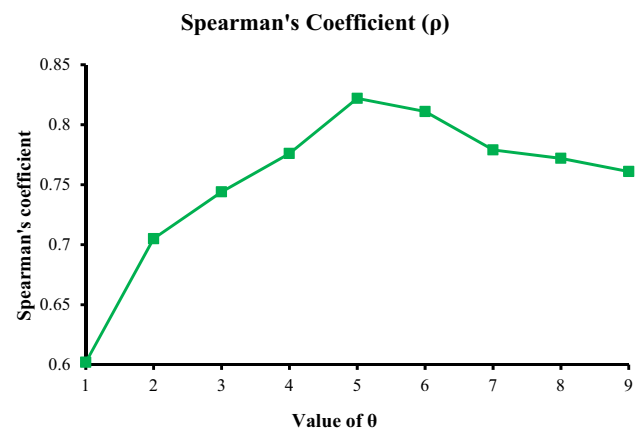

Fig. 5 Sensitivity analysis of θ

function (i.e., convex part) decreases [41]. It means that DMs become less sensitive to the loss with an increase in θ; in simple words, the lower degree of loss corresponds to the greater value of θ [66]. The observed and the compared ranks are then compared using the Spearman's rank correlation coefficient rho (ρ). If ρ is greater than 0.7, then the correlation is highly positive [67]. The higher the value of (ρ), better is the relation. For $\theta > 9$, no significant difference is seen in the rankings, while for $\theta = 8$ and 9, the ranking is almost the same.

The highest value for ρ is found to be 0.822 at $\theta = 5$, as shown in Fig. 5. Thus, it can be said that for predicting the results using TODIM based on collected user responses, $\theta = 5$ is the optimum value to match drivers' psychological behavior. It reflects that the prospect value graph for $\theta = 5$ clearly represents the loss aversion by the DMs. In terms of the physical sense of this value, it represents the relation between the losses and gain. In simple words, at the value of $\theta = 5$, the DMs become less sensitive toward losses (as compared to $\theta = 1$), and thus, they tend to choose the desired lanes with the maximum number of lane changes to decrease their delay. Furthermore, the higher value of θ means that the driver gets promoted to change the lanes [50] and decide the lane by evaluating the

Table 7 Results for TODIM

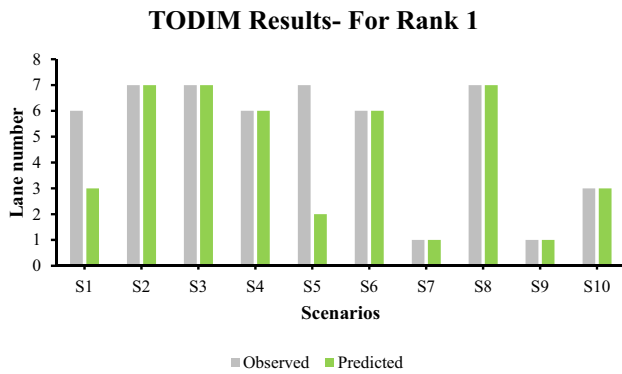| Alternative	Partial matrix of dominance $\delta\,(Ai,Aj) = \sum_{c=1}^{m}\Phi c(Ai,Aj)$	Final matrix of dominance $\xi_i = \dfrac{\sum_{j=1}^{n}\delta(Ai,Aj)-\min\sum_{j=1}^{n}\delta(Ai,Aj)}{\max\sum_{j=1}^{n}\delta(Ai,Aj)-\min\sum_{j=1}^{n}\delta(Ai,Aj)}$	Predicted rank	Observed rank
Lane 1	− 1.823	0.015	2	2
Lane 2	0.207	0.447	4	3
Lane 3	2.580	0.952	6	6
Lane 4	2.806	1.000	7	7
Lane 5	− 0.074	0.387	3	4
Lane 6	0.577	0.525	5	5
Lane 7	− 1.892	0.000	1	1

Fig. 6 Results for other scenarios (Rank 1)

criteria (such as lane with the minimum number of vehicles in the queue or with less proportion of heavy vehicles) in the front space (i.e., flare area in the diverging zone of toll plaza). It illustrates the risk-seeking behavior of the DMs when presented with the gain.

Step 5: Final dominance matrix of general element (Ai, Aj) is obtained through the sum of the diverse matrix

$$\xi_i = \frac{\sum_{j=1}^{n} \delta(Ai, Aj) - \min \sum_{j=1}^{n} \delta(Ai, Aj)}{\max \sum_{j=1}^{n} \delta(Ai, Aj) - \min \sum_{j=1}^{n} \delta(Ai, Aj)}. \quad (13)$$

Rank the alternative based on ξ values (global utility value) in increasing order (using Eq. 13). As for the minimum delay, the factors should be as least as possible; hence, the numbering is done in ascending order, as shown in Table 7. Here, the priority is given to Lane 7. As observed from Fig. 3, Lane 7 has the smallest queue with only one vehicle, and with no proportion of heavy vehicles and trailers, the maximum responses give the choice of lane 7 only, and the same has been predicted by the algorithm.

The same procedure is repeated for different scenarios on field conditions, and the predicted ranks are estimated. Ten field conditions are considered, and the ranks for the alternatives are determined using the TODIM method. Here, the first six scenarios were used for calibration of θ, and from that, the value of θ is obtained as 5. After that, the last four scenarios were used for validation, and the results show the perfect matching of the ranks. Figure 6 shows the prediction for Rank 1 using TODIM, and from that, it can be concluded that the TODIM can be used to predict the rankings for choosing the toll lanes.

Contribution of the Present Study

The study investigates the lane choice behavior of driver's using MCDM method. In the present practice, there as many studies related to traffic operation and safety using a driving

simulator [68–73]. Different scenarios are generated for the driving simulator studies to mimic the field conditions using different car-following models and lane-changing/choice models. The car-following behavior is used mostly for longitudinal directional movement, while the lane-changing/lane choice behavior is used for lateral movements. Various car-following models, such as Gipps Model, Pipes Model, etc. [74], were developed in the past and are widely used for developing scenarios. However, the lane choice models were not well explored in the literature for the driving simulator and simulation studies [75], and hence, this study can fill the available gap, and such lane choice module may be provided in the driving simulator or in the simulation studies. Furthermore, autonomous vehicles are also penetrating the traffic flow and thus causing the mixed nature of human-driven and self-driving vehicles in a particular traffic stream. In such conditions, the autonomous vehicles have to decide to pass through a particular toll lane for paying the toll [11], and such module of lane choice may be provided in those vehicles as the application of the present study. In the field also, if such information may be transferred to the approaching vehicles using advanced technology such as Intelligent Transportation Systems (ITS), then the vehicle may proceed to select the given lane and make its path in that way. This will reduce his/her delay and subsequently result in better traffic operations with maximum safety of the road users.

Conclusions and Way Forward

In the present study, an attempt is made to model the lane choice behavior of drivers at toll plazas based on user perception and the MCDM method. TODIM method is applied to predict the rakings for choosing the toll lane using the AHP weights. From the user's perception and AHP methodology, the most influencing factor affecting the lane choice at toll plaza among the given criteria is found out. It is seen that number of vehicles in the queue has the highest weight, followed by the proportion of heavy vehicles, the proportion of trailers, and the number of lane changes, respectively. Thus, it can be concluded that the users prefer the shortest lane.

After obtaining the weights of different criteria, the TODIM methodology is used to rank toll lanes. The psychological behavior of the driver is varying, and hence, the value of loss aversion factor θ must be fixed according to the TODIM method. For fixing the θ value, the concept of rank correlation is used. The observed ranks, i.e., obtained by the user's perception survey and the predicted ranks from TODIM, are compared using Spearman's correlation coefficient. The Spearman's rank correlation coefficient for $\theta = 5$ is 0.822, which is the maximum of than other values of θ. It means that for the value of $\theta = 5$, the psychological behavior

of the driver is perfectly correlated and matching, and the correlation coefficient is highly positive, which shows a strong correlation between the observed and the predicted ranks.

The user perception method of TODIM can be used to develop an application for generating the output based on available criteria and alternatives is developed. The application will inform the driver about which lane he/she should choose to avoid delay at the toll plaza prior to reaching the toll plaza. The application will work on real-time data and the use of image processing. Furthermore, it will help to develop a proper simulation model for mixed traffic conditions. Moreover, the penetration of autonomous vehicles is increasing worldwide; the present study will act as a base model for autonomous vehicles for lane choice at toll plazas under prevailing traffic conditions. Furthermore, as observed in the literature, a number of safety studies are undertaken with the help of a driving simulator, and hence, there is a need to generate scenarios that clearly represent the real field conditions. Though car-following models can handle the longitudinal movements, the lane choice can be made with the help of the present study's proposed methodology. This can help to increase the reliability and accuracy of safety and behavioral study investigations carried using driving simulators. Also, the driving simulators act as a driving environment for autonomous vehicles which can further help to train them properly. The present study is limited to the lane choice behavior of car users only. Similar perceptions may also be received from other vehicle drivers to develop a more robust lane choice model.

Declarations

Conflict of Interest On behalf of all authors, the corresponding author states that there is no conflict of interest.

References

1. Bari CS, Kumawat A, Dhamaniya A (2021) Effectiveness of FASTag system for toll payment in India. Present 7th Int IEEE Conf Model Technol Intell Transp Syst 16–17 p 1–6.

2. Bari CS, Chandra S, Dhamaniya A et al (2021) Service time variability at manual operated tollbooths under mixed traffic environment: towards level-of-service thresholds. Transp Policy 106:11–24. https://doi.org/10.1016/j.tranpol.2021.03.018

3. Bari C, Navandar Y, Dhamaniya A (2019) Service time variation analysis at manually operated toll plazas under mixed traffic conditions in India. J East Asia Soc Transp Stud 13:331–350

4. Bari CS, Navandar YV, Dhamaniya A (2020) Vehicular emission modeling at toll plaza using performance box data. J Hazard Toxic Radioact Waste 24:1–19. https://doi.org/10.1061/(ASCE)HZ.2153-5515.0000550

5. Dubedi A, Chakroborty P, Kundu D, Reddy KH (2012) Modeling automobile drivers' toll-lane choice behavior at a toll plaza. J Transp Eng 138:1350–1357. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000440

6. Li A, Sun L, Zhan W, Tomizuka M (2019) Multiple criteria decision-making for lane-change model. Comput Sci Eng, pp 1–7

7. Chakroborty P, Gill R, Chakraborty P (2016) Analysing queueing at toll plazas using a coupled, multiple-queue, queueing system model: application to toll plaza design. Transp Plan Technol Taylors Fr. https://doi.org/10.1080/03081060.2016.1204090

8. Mudigonda S, Bartin B, Ozbay K (2008) microscopic modeling of lane selection and lane-changing at toll plazas. In: 88th Annu Meet Transp Res Board, Washington, DC Transportation Res 855: 1–18

9. Lin F-B, Su C-W (1994) Level of service analysis of toll plazas on freeway main lines. J Transp Eng 120:246–263

10. Gulewicz V, Danko J (1995) Simulation-based approach to evaluating optimal lane staffing requirements for toll plazas. Transp Res Rec J Transp Res Board 1484:33–39

11. Yu B, Mwaba D (2020) Toll plaza lane choice and lane configuration strategy for autonomous vehicles in mixed traffic. J Transp Eng Part A Syst ASCE 146:1–11. https://doi.org/10.1061/JTEPBS.0000457

12. Mekić A (2019) Multi-criteria decision making for improvement of security and efficiency at airport security checkpoints using agent-based models. Technische Universiteit Delft

13. Marqués AI, García V, Sánchez JS (2020) Ranking-based MCDM models in financial management applications: analysis and emerging challenges. Prog Artif Intell 9:171–193. https://doi.org/10.1007/s13748-020-00207-1

14. Marsh K, Ijzerman M, Thokala P et al (2016) Multiple Criteria decision analysis for health care decision making-emerging good practices: report 2 of the ISPOR MCDA Emerging Good Practices Task Force. Value Health. https://doi.org/10.1016/j.jval.2015.12.016

15. Le PM, Marcucci E, Gatta V, Ignaccolo M (2017) Towards a decision-support procedure to foster stakeholder involvement and acceptability of urban freight transport policies. Eur Transp Res Rev 9:1–14. https://doi.org/10.1007/s12544-017-0268-2

16. Ogu MI (2013) Rational choice theory: assumptions, strengths, and greatest weaknesses in applications outside the western Milieu context. Arab J Bus Manag Rev (Nigerian Chapter) 1:90–99

17. Tian X, Niu M, Ma J, Xu Z (2020) A Novel TODIM with probabilistic hesitant fuzzy information and its application in green supplier selection. Complexity. https://doi.org/10.1155/2020/2540798

18. Liu P, You X (2019) Improved TODIM method based on linguistic neutrosophic numbers for multicriteria group decision-making. Int J Comput Intell Syst 12:544–556. https://doi.org/10.2991/ijcis.d.190412.001

19. Haddad M, Sanders D (2018) Selection of discrete multiple criteria decision making methods in the presence of risk and uncertainty. Oper Res Perspect 5:357–370

20. Keeney RL, Raiffa H (1993) Decisions with multiple objectives: preferences and value trade-offs. Cambridge University Press

21. Alsalem MA, Zaidan AA, Zaidan BB et al (2018) Systematic review of an automated multiclass detection and classification system for acute leukaemia in terms of evaluation and benchmarking, open challenges, issues and methodological aspects. J Med Syst 42:1–36. https://doi.org/10.1007/s10916-018-1064-9

22. Mardani A, Jusoh A, Nor KMD et al (2015) Multiple criteria decision-making techniques and their applications—a review of the literature from 2000 to 2014. Econ Res Istraz 28:516–571. https://doi.org/10.1080/1331677X.2015.1075139

23. Howard S, Scott IA, Ju H et al (2019) Multicriteria decision analysis (MCDA) for health technology assessment: the Queensland Health experience. Aust Heal Rev 43:591–599. https://doi.org/10.1071/AH18042

24. Rao VR (2006) Decision making in the manufacturing environment using graph theory and fuzzy multiple attribute decision making methods. Springer

25. Ananda J, Herath G (2009) A critical review of multi-criteria decision making methods with special reference to forest management and planning. Ecol Econ 68:2535–2548. https://doi.org/10.1016/j.ecolecon.2009.05.010

26. Wątróbski J, Jankowski J, Ziemba P et al (2019) Generalised framework for multi-criteria method selection. Omega (United Kingdom) 86:107–124. https://doi.org/10.1016/j.omega.2018.07.004

27. Eldrandaly K, Ahmed HA, AbdelAziz N (2009) An expert system for choosing the suitable MCDM method for solving a spatial decision problem. In: 9th International Conference on production engineering, design and control, p 12

28. Triantaphyllou E, Sánchez A (1997) A sensitivity analysis approach for some deterministic multi-criteria decision-making methods. Decis Sci 28:151–194. https://doi.org/10.1111/j.1540-5915.1997.tb01306.x

29. Romero C, Rehman T (2003) Chapter six The interactive multiple criteria decision-making approach. Dev Agric Econ 11:79–102. https://doi.org/10.1016/S0926-5589(03)80008-0

30. Vanderpooten D (1989) The interactive approach in MCDA: a technical framework and some basic conceptions. Math Comput Model 12:1213–1220. https://doi.org/10.1016/0895-7177(89)90363-4

31. Binetti M, Borri D, Circella G, Mascia M (2005) Does prospect theory improve understanding of transit user behaviour. In: In: Proceedings of the 9th Conference CUPUM, computer in urban planning and urban management, London, UK. pp 1–12

32. Gomes LFAM, Lima MMPP (1991) TODIM: basic and application to multicriteria ranking of projects with environmental impacts. Found Comput Decis Sci 16:113–127

33. van de Kaa EJ (2010) Prospect theory and choice behaviour strategies: Review and synthesis of concepts from social and transport sciences. Eur J Transp Infrastruct Res 10:299–329. https://doi.org/10.18757/ejtir.2010.10.4.2897

34. Kahneman D, Tversky A (1979) Prospect theory: an analysis of decision under risk. Econometrica 47:263–291

35. Allias M (1953) Le Comportement de l'Homme Rationnel devant le Risque : Critique des Postulats et Axiomes de l'Ecole Americaine. Econometrica 21:503–546

36. Dubedi A, Chakroborty P, Kundu D et al (2012) Modeling automobile drivers' toll-lane choice behavior at a toll plaza. J Transp Eng ASCE 138:1350–1357. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000440

37. Lin F-B, Cheng-Wei Su (1994) Level-of-service analysis of toll plaza on freeway mainlines. J Transp Eng 120:246–263

38. Hill C, Elefteriadou L, Kondyli A (2015) Exploratory analysis of lane changing on freeways based on driver behavior. J Transp Eng ASCE. https://doi.org/10.1061/(ASCE)TE.1943-5436.0000758

39. Lourenzutti R, Krohling RA (2015) TODIM based method to process heterogeneous information. Proc Comput Sci 55:318–327. https://doi.org/10.1016/j.procs.2015.07.056

40. Autran Monteiro Gomes LF, Duncan Rangel LA (2009) An application of the TODIM method to the multicriteria rental evaluation of residential properties. Eur J Oper Res 193:204–211. https://doi.org/10.1016/j.ejor.2007.10.046

41. Gomes LFAM, Rangel LAD, Maranhão FJC (2009) Multicriteria analysis of natural gas destination in Brazil: an application of the TODIM method. Math Comput Model 50:92–100. https://doi.org/10.1016/j.mcm.2009.02.013

42. Rangel LAD, Gomes LFAM, Cardoso FP (2011) An application of the TODIM method to the evaluation of Broadband Internet plans. Pesqui Oper 31:235–249. https://doi.org/10.1590/S0101-74382011000200003

43. Gomes LFAM, Machado MAS, Rangel LAD (2013) Behavioral multi-criteria decision analysis: The TODIM method with criteria interactions. Ann Oper Res 211:531–548. https://doi.org/10.1007/s10479-013-1345-0

44. Tian X, Niu M, Zhang W, Li L (2021) A novel TODIM based on prospect theory to select green supplier with Q-rung orthopair fuzzy set. Technol Econ Dev Econ 27:284–310

45. Zhang S, Wu Z, Ma Z et al (2021) Wasserstein distance-based probabilistic linguistic TODIM method with application to the evaluation of sustainable rural tourism potential. Econ Res Istraz. https://doi.org/10.1080/1331677X.2021.1894198

46. Ding Q, Wang YM, Goh M (2021) TODIM dynamic emergency decision-making method based on hybrid weighted distance under probabilistic hesitant fuzzy information. Int J Fuzzy Syst 23:474–491. https://doi.org/10.1007/s40815-020-00978-8

47. Zhang D, Zhao M, Wei G, Chen X (2021) Single-valued neutrosophic TODIM method based on cumulative prospect theory for multi-attribute group decision making and its application to medical emergency management evaluation. Econ Res Istraž. https://doi.org/10.1080/1331677x.2021.2013914

48. Farooq D, Moslem S, Jamal A et al (2021) Assessment of significant factors affecting frequent lane-changing related to road safety: an integrated approach of the AHP-BWM model. Int J Environ Res Public Health 18:1–17. https://doi.org/10.3390/ijerph182010628

49. Sun R, Li M, Wu Q (2018) Research on commuting travel mode choice of car owners considering return trip containing activities. Sustain MDPI 10:1–12. https://doi.org/10.3390/su10103494

50. Long X, Zhang L, Liu S, Wang J (2020) Research on decision-making behavior of discretionary lane-changing based on cumulative prospect theory. J Adv Transp. https://doi.org/10.1155/2020/1291342

51. Indian Roads Congress (IRC): SP: 84 (2019) Manual of Specifications and Standards for Four Laning of Highways (Second Revision), New Delhi, India

52. Tversky A, Kahneman D (1991) Loss aversion in riskless choice: a reference-dependent model. Q J Econ 106:1039–1061

53. Tversky A, Kahneman D (1992) Advances in prospect theory: cumulative representation of uncertainty. J Risk Uncertain 5:297–323

54. Abdellaoui M, Bleichrodt H, Paraschiv C (2007) Loss aversion under prospect theory: a parameter-free measurement. Manag Sci 53:1659–1674. https://doi.org/10.1287/mnsc.1070.0711

55. Wakchaure SS, Jha KN (2012) Determination of bridge health index using analytical hierarchy process. Constr Manag Econ 30:133–149. https://doi.org/10.1080/01446193.2012.658075

56. Vaidya OS, Kumar S (2006) Analytic hierarchy process: an overview of applications. Eur J Oper Res 169:1–29. https://doi.org/10.1016/j.ejor.2004.04.028

57. Saaty RW (1987) The analytic hierarchy process-what it is and how it is used. Mathi Model 9:161–176

58. Holguín-Veras J (1995) Comparative assessment of AHP and MAV in highway planning: case study. J Transp Eng 121:191–200. https://doi.org/10.1061/(ASCE)0733-947X(1995)121:2(191)

59. He H, Li Y, Zhang Z (2016) Scheme optimization of large-scale highway transport based on AHP-grey correlation degree. J Highw Transp Res Dev 10:98–102

60. Taherdoost H (2017) Decision making using the analytic hierarchy process (AHP); A step by step approach. Int J Econ Manag Syst 2:244–246

61. Lidinska L, Jablonsky J (2018) AHP model for performance evaluation of employees in a Czech management consulting company. Cent Eur J Oper Res 26:239–258. https://doi.org/10.1007/s10100-017-0486-7

62. Saaty TL (2008) Decision making with the analytic hierarchy process. Int J Serv Sci 1:83–98. https://doi.org/10.1016/0305-0483(87)90016-8

63. Yin J, Guo J, Ji T et al (2019) An extended TODIM Method for project Manager's Competency Evaluation. J Civ Eng Manag 25:673–686

64. Llamazares B (2018) An analysis of the generalized TODIM method An analysis of the generalized TODIM method. Eur J Oper Res. https://doi.org/10.1016/j.ejor.2018.02.054

65. Wang F, Li H (2015) Novel method for hybrid multiple attribute decision making based on TODIM method. J Syst Eng Electron 26:1023–1031. https://doi.org/10.1109/JSEE.2015.00111

66. Dehaghi BF, Khoshfetrat A (2020) Modified TODIM method for water reuse application: a case study from Iran. Desalin Water Treat 195:186–200. https://doi.org/10.5004/dwt.2020.25844

67. Mukaka MM (2012) Statistics corner: a guide to appropriate use of Correlation coefficient in medical research. Malawi Med J 24:69–71

68. Buzon LG, Figueira AC, Larocca APC, Oliveira PTMS (2021) Effect of speed on driver's visual attention: a study using a driving simulator. Transp Dev Econ 8:1–11. https://doi.org/10.1007/s40890-021-00139-y

69. Pawar NM, Velaga NR (2022) Analyzing the impact of time pressure on drivers' safety by assessing gap-acceptance behavior at un-signalized intersections. Saf Sci 147:105582. https://doi.org/10.1016/j.ssci.2021.105582

70. Pawar NM, Khanuja RK, Choudhary P, Velaga NR (2020) Modelling braking behaviour and accident probability of drivers under increasing time pressure conditions. Accid Anal Prev 136:105401. https://doi.org/10.1016/j.aap.2019.105401

71. Saad M, Abdel-Aty M, Lee J (2019) Analysis of driving behavior at expressway toll plazas. Transp Res Part F Traffic Psychol Behav 61:163–177. https://doi.org/10.1016/j.trf.2017.12.008

72. Sadia R, Bekhor S, Polus A (2018) Structural equations modelling of drivers' speed selection using environmental, driver, and risk factors. Accid Anal Prev 116:21–29. https://doi.org/10.1016/j.aap.2017.08.034

73. Choudhari T, Maji A (2021) Risk assessment of horizontal curves based on lateral acceleration index: a driving simulator-based study. Transp Dev Econ 7:1–11. https://doi.org/10.1007/s40890-020-00111-2

74. Raju N, Arkatkar S, Easa S, Joshi G (2021) Customizing the following behavior models to mimic the weak lane based mixed traffic conditions. Transp B. https://doi.org/10.1080/21680566.2021.1954562

75. Bains MS, Arkatkar SS, Anbumani KS, Subramaniam S (2017) Optimizing and modeling tollway operations using microsimulation case study Sanand Toll Plaza, Ahmedabad, Gujarat, India. Transp Res Rec J Transp Res Board 2615:43–54. https://doi.org/10.3141/2615-06

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.