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A Mathematical Model Proposal for The Optimal Distribution of Traffic Units to Locations: CRITIC-Based Curve Estimations (CBCE)

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Abstract

The presence of traffic enforcement units is widely recognized as a critical factor in reducing traffic accidents. Therefore, the optimal allocation of these units holds substantial importance for ensuring the efficient use of resources, minimizing accident rates, and enhancing overall road safety. In this study, a mathematical method called the CRITIC-Based Curve Estimation (CBCE) approach is proposed to achieve the optimal distribution of traffic units across regions. To ensure the applicability of the proposed model, the factors influencing traffic accidents (independent variables) were identified based on both expert opinions and an extensive review of the relevant literature. The numerical data representing regional traffic characteristics were constructed using hypothetical samples. Quantitative values for these factors were assigned for two regions, and a decision matrix was developed accordingly. The weights of the identified factors were calculated using the CRITIC method, while their effects on traffic accidents were analyzed through the Curve Estimation technique. As a result of these analyses, optimal allocation ratios for traffic enforcement units across regions were determined. Empirical findings indicate that the proposed method yields ideal results in sensitivity analyses, demonstrates stability and reliability in comparative evaluations, and produces robust and consistent outputs in simulation-based tests. The proposed approach is expected to provide valuable insights for both the public and private sectors in developing effective traffic management and safety strategies.

Keywords: traffic units, CRITIC, CRITIC-Based Curve Estimation, optimal distribution ratio

Trafik Birimlerinin Lokasyonlara Optimal Dağılımı İçin Bir Matematiksel Model Önerisi: CRITIC Tabanlı Eğri Tahminleri (CBCE)

Öz

Trafik denetim birimlerinin varlığı, trafik kazalarının azaltılmasında önemli bir faktör olarak kabul edilmektedir. Bu nedenle, trafik birimlerinin optimal dağılımı, kaynakların verimli kullanımı, kazaların azaltılması ve yol güvenliğinin artırılması açısından kritik bir öneme sahiptir. Bu çalışmada, bölgeler arasında trafik birimlerinin optimal dağılımını sağlamak için CRITIC Tabanlı Eğri Tahmini (CBCE) adı verilen matematiksel bir yöntem önerilmiştir. Yöntemin uygulanabilirliğini sağlamak amacıyla, trafik kazalarını etkileyen faktörler (bağımsız değişkenler) trafik uzmanlarının görüşleri ve literatür taraması doğrultusunda belirlenmiştir. Çalışmada bölgelerin trafik ile ilgili sayısal değerleri hipotetik örneklemlere dayanmaktadır. Bu faktörlere ait nicel değerler iki bölge için atanmış ve bir karar matrisi oluşturulmuştur. Belirlenen faktörlerin ağırlıkları CRITIC yöntemi kullanılarak hesaplanmış ve bu faktörlerin trafik kazaları üzerindeki etkileri Eğri Tahmini yöntemi ile analiz edilmiştir. Bu analizlerin sonucunda, bölgeler için optimal trafik birimi tahsis oranları belirlenmiştir. Ampirik bulgular, önerilen yöntemin duyarlılık analizlerinde ideal sonuçlar verdiğini, karşılaştırmalı analizlerde kararlı ve güvenilir olduğunu ve simülasyon analizlerinde sağlam ve tutarlı çıktılar sunduğunu göstermektedir. Çalışmada önerilen yöntemin hem kamu hem de özel sektör tarafından trafik stratejilerinin geliştirilmesi açısından faydalı olacağı düşünülmektedir.

Anahtar Kelimeler: trafik birimleri, CRITIC, CRITIC Tabanlı Eğri Tahmini, optimal dağılım oranı

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A Mathematical Model Proposal for The Optimal Distribution of Traffic Units to Locations: CRITIC-Based Curve Estimations (CBCE)

1. Introduction

Traffic, as an indispensable component of modern society, underpins social, economic, and cultural continuity (Wang et al., 2023; Rivers, 2011). Ensuring its safe and sustainable operation is therefore vital for societal well-being, as disruptions not only cause individual harm but also broader socio-economic consequences (Kumar, 2023; Dausan & Barican, 2024). Traffic accidents generate substantial economic losses through medical costs, productivity decline, and infrastructure damage, underscoring the strategic importance of traffic safety for both public welfare and national development (Schoeters et al., 2020; Sinha et al., 2021; Hall et al., 2024). Consequently, the enforcement of traffic laws represents a fundamental mechanism for minimizing accidents and enhancing overall safety (Ergin & Güler, 2024).

In this context, the operational efficiency of traffic enforcement agencies is crucial to maintaining order and ensuring compliance on road networks (Adler, 2014). Inspections targeting major risk factors such as speeding, alcohol consumption, and inattentive driving play a pivotal role in accident prevention (Sümer & Kaygısız, 2014). Moreover, the spatially optimized allocation and frequency of enforcement activities are essential, particularly in high-risk regions, to achieve meaningful reductions in accident incidence (Syah, 2024; Jasvi, 2024). Thus, the optimal geographic distribution of enforcement units can be considered a cornerstone of sustainable traffic safety management (Meduri et al., 2023).

Building upon these foundations, the present study develops a mathematical model to determine the optimal allocation of traffic enforcement units across regions, employing a hypothetical dataset derived from expert evaluations. The model identifies region-specific accident determinants and quantifies their relative importance through the CRITIC (CRiteria Importance Through Intercriteria Correlation) weighting method, which accounts for both variability and interdependence among criteria. Subsequently, the functional relationships between traffic variables and accident rate (TIV) are modeled via the Curve Estimation technique, facilitating a statistically and mathematically grounded framework for enforcement unit distribution.

The study's structure is organized as follows: the literature review discusses key concepts of traffic safety, accident dynamics, and enforcement impacts; the methodology section details dataset construction, CRITIC-based weighting, and model formulation; and the results section presents quantitative findings validated through sensitivity, comparative, and simulation analyses. Finally, the discussion synthesizes these outcomes, evaluating the robustness, applicability, and theoretical contributions of the proposed model to the field of traffic safety optimization.

2. Literature

Traffic safety encompasses coordinated measures and practices aimed at minimizing accidents, injuries, and fatalities within the transportation system (Shinar, 2017). It depends on the effective interaction among people, vehicles, and infrastructure, each component playing a crucial preventive role (Kockott, 2021). Furthermore, the enforcement of laws, regulations, and standards by governmental authorities is essential to ensuring compliance and maintaining safety for all road users (Ortiz & Bennett, 2018). The efficiency of such enforcement activities significantly influences overall safety outcomes (Zhang et al., 2013), as the presence of traffic units encourages driver vigilance and responsible behavior (Sum & Ortiz, 2024).

Regular inspections such as alcohol tests, speed checks, and vehicle or document controls heighten drivers' awareness of enforcement, deter rule violations, and enhance compliance (Nguyen-Phuoc et al., 2024). These practices not only penalize offenders but also serve as a psychological deterrent for others, thereby promoting safer behavior and reducing accident risks (Sidha et al., 2021; Sam, 2022). Consequently, increasing both the number and effectiveness of traffic enforcement units is critical to improving road safety outcomes (Bradford et al., 2015).

Despite the acknowledged importance of enforcement, no prior research has quantitatively determined the optimal number of traffic units required for different regions (Berhanu et al., 2023). Nonetheless, several studies have demonstrated the positive effects of inspections and penalties on accident reduction. For instance, Sümer and Kaygısız (2014, 2015) showed that inspections and penalties decreased nationwide accidents in Türkiye by roughly 10%. Rahimi et al. (2017) emphasized that effective enforcement heightens driver awareness, while Wahi et al. (2018) found that intensified intersection inspections reduced bicycle and motorcycle accidents in Queensland. Similarly, Beenstock et al. (2001) and Elvik et al. (2022) demonstrated, through long-term analyses in Israel and Norway respectively, that increased inspection frequency and duration significantly reduce accident rates. Kılıç and Asal (2024) further used MCDM techniques (MAUT, AHP, TOPSIS) to identify the most effective inspection types, finding that those targeting public transportation safety were most beneficial. Complementarily, Çavdar et al. (2018) highlighted the role of intelligent speed control systems in improving safety.

Regarding accident determinants, multiple studies have identified key contributing factors. Eygü (2018) and Tercan and Beşdok (2018) demonstrated the influence of spatial, temporal, and environmental conditions on accidents, while Gorzelańczyk and Piątkowski (2024) emphasized weather-related impacts. Other research underscored the significance of driver behavior, road geometry, and vehicle characteristics (Rolison, 2020; Bucsuházy et al., 2020; Safari et al., 2019; Dong et al., 2020; Yakupova et al., 2020; Hossain, 2021; Zeng et al., 2024). Structural and geological attributes of cities have also been identified as persistent contributors to accident frequency (Yang, 2024; Abuzinadah et al., 2024; Wang et al., 2023; Berhanu et al., 2023). Finally, studies emphasize that the adverse effects of human-related factors can be mitigated through consistent and effective enforcement strategies, which reinforce compliance and reduce behavioral risks (Hu et al., 2020; Modipa, 2022).

3. Material and Method

3.1. Dataset and Analysis of the Study

In the study, the traffic criteria used for the optimal distribution of traffic units across regions were established based on the input of 15 traffic experts, hypothetical regions and hypothetical values over four years were assigned to two regions (Region A and Region B). The data presented in this study were artificially generated solely for the purpose of illustrating the proposed methodological framework. The identified criteria are less likely to be fixed factors, as they primarily reflect the characteristics of the road quality. According to the experts consulted and literature, human factors were excluded from the criteria due to their highly variable nature, as these factors could introduce temporal and spatial inconsistencies in their impact on traffic accidents (Dekker, 2002; Useche et al., 2018).

Furthermore, it is particularly challenging to predict under which circumstances drivers take risks and/or make errors that may lead to unsafe situations and, ultimately, to accidents (Schakel et al., 2016). This variability makes the influence of human factors on traffic accidents more relative, particularly in terms of driver behavior and driving quality. Therefore, the traffic criteria identified through expert opinions exhibit less variability over time compared to human-factor-related variables, and they are common variables that all drivers encounter or may encounter in a demographic sense. Additionally, as noted in the literature, expert opinions suggest that traffic enforcement and visibility by traffic units would naturally increase drivers' sensitivity to traffic issues. This would, in turn, directly influence drivers' adherence to traffic rules and enhance their ability to maintain safe traffic positions. The criteria formed based on traffic expert opinions and supported by literature are explained in detail as follows.

Annual Traffic Density (T1-Independent Variable, number of vehicles) (Hossain, 2021): Traffic density is a significant factor contributing to traffic accidents, as heavy traffic reduces the distance between vehicles, thereby increasing the risk of collisions. Additionally, drivers under stressful and hurried conditions are more likely to engage in risky behaviors, further exacerbating accident rates. Consequently, it is crucial for traffic enforcement units to consider traffic density in their planning processes. Effective enforcement during peak hours and in high-density areas, along with proper traffic flow regulations and guidance measures, can help mitigate accident risks. Developing strategies based on regional traffic density is essential for traffic enforcement units to prevent accidents and ensure safe transportation. As shown in Equation 1, the traffic density of a given region can be calculated as the annual vehicle traffic, determined by multiplying the average daily number of vehicles on the road by 365.

ANV: The daily average number of vehicles on the road

$$T1 = ANV.365\ (number\ of\ vehicles) \tag{1}$$

Total Road Network (T2-Independent Variable, km) (Wang et al., 2019): The total length of the road network in a region has a significant impact on the frequency of traffic accidents. Extensive road networks can increase the likelihood of accidents due to the inclusion of various road conditions, intersections, and traffic density variables. Planning based on the total road network allows traffic enforcement units to implement effective measures in areas where accidents are concentrated. Specifically, improving road infrastructure, conducting regular inspections, and enhancing traffic safety measures can help reduce accidents. In this context, developing strategic plans by incorporating road network data is a critical factor for traffic enforcement units in ensuring traffic safety. Accordingly, the formula for calculating the total road network is presented in Equation 2.

$$T2 = TRN\ (km.) \tag{2}$$

Physical Characteristics of Roads (PCR) (T3-Independent Variable) (Yakupova et al., 2020): The physical characteristics of roads, such as the total number of sloped roads and their average gradient, as well as the number of curved roads and their average curvature angle, significantly influence traffic accidents in a region. Sloped and curved roads increase driving challenges, particularly under adverse weather conditions or heavy traffic, thereby heightening the risk of accidents. As a result, it is crucial for traffic enforcement units to focus on these types of roads by implementing safety measures such as speed limits, warning signs, and road maintenance. Effective traffic enforcement on these roads plays a critical role in reducing accident rates and improving overall road safety. Accordingly, the calculation related to the physical characteristics of roads is detailed in Equation 3.

$SDEG$: Slope degree (The vertical distance is taken into consideration in the analysis),

SRD: Slopes Road distance (km),

$CDEG$: Curve degree,

CRD: Curve road distance (km).

$$T3\ ((PCR) = km.) = SDEG.SRD + CDEG.CRD \tag{3}$$

Annual Regional Population (ARP) (T4-Independent Variable) (Berhanu et al., 2023): Regional population can directly influence the frequency of traffic accidents. As population density increases, road usage and traffic flow become more congested, thereby elevating the risk of accidents. Furthermore, population characteristics can impact driver behavior and traffic safety culture. In this context, the importance of traffic enforcement is substantial. Implementing effective traffic control and safety measures in densely populated areas plays a critical role in preventing accidents and ensuring a safe transportation environment. Developing strategies based on regional population density enables enforcement units to enhance traffic safety and adopt effective approaches to reduce accidents. The equation describing T4 is presented in Equation 4.

TP: Total population

$$T4\ (ARP) = \frac{TP}{T2} \tag{4}$$

Annual Industrial and Commercial Activities (AICA) (T5-Independent Variable) (Zeng et al., 2024): Industrial and commercial activities in a region can significantly impact the frequency of traffic accidents. In areas with intense industrial and commercial operations, the number of transport vehicles increases, leading to higher traffic density and elevated accident risks. Additionally, factors such as hurried driving behaviors and high-speed travel in these areas can further exacerbate the likelihood of accidents. Thus, traffic enforcement plays a crucial role in regions with high industrial and commercial activity. Effective traffic monitoring, enforcement of speed limits, regulation of freight transport rules, and enhancement of road safety measures are essential in reducing accident rates. Additionally, although the variables T1 (Annual Traffic Density) and T5 (Annual Industrial and Commercial Activities) may appear to reflect similar dynamics, they in fact represent conceptually distinct dimensions. The T1 variable exclusively captures the volume and intensity of vehicular traffic within a region (e.g., number of vehicles, vehicle-kilometers, traffic flow), whereas T5 reflects the level of economic production and commercial activity in the same area (e.g., industrial production index, trade volume, number of enterprises).

Accordingly, T1 represents transport-related mobility, while T5 denotes the intensity of economic activity two independent constructs in terms of both content and measurement. Moreover, potential multicollinearity between these variables was statistically examined by assessing tolerance and

TIV values, and no significant overlap was detected. Therefore, the inclusion of both variables within the model does not adversely affect its explanatory validity or robustness. The calculation for industrial and commercial activities in a region is outlined in Equation 5.

ICV: The daily average number of industrial and commercial vehicles on the road.

$$T5(AICA = number\ of\ vehicles) = ICV.365 \quad (5)$$

Annual Tourism Potential (T6-Independent Variable) (Abuzinadah et al., 2024): Tourism potential in a region, particularly an increase in the number of tourists, can influence the frequency of traffic accidents. Tourists may have different road knowledge and driving habits compared to local drivers, which can elevate accident risks. Intense tourist activities and vehicle traffic, especially during holiday seasons, often contribute to an increase in accidents. Therefore, traffic enforcement is of paramount importance in areas with high tourism potential. Strategies such as effectively communicating traffic rules to tourists, enforcing speed controls, and implementing specialized safety measures are crucial to ensuring tourist safety. The variable T6 (Annual Tourism Potential) serves as a socioeconomic indicator that indirectly influences the spatial distribution of traffic enforcement units. This variable represents regional patterns of touristic activity, visitor density, and seasonal population fluctuations. In regions with high tourism potential, vehicle traffic typically increases significantly during specific periods of the year, directly affecting both the spatial allocation and the operational frequency of traffic enforcement units. Therefore, although T6 is not a direct traffic indicator, it functions as a determinant socioeconomic factor influencing traffic demand, density distribution, and enforcement planning, and is thus incorporated into the model. Particularly in tourism-oriented or coastal areas where seasonal surges in mobility occur, this variable enhances the spatial realism of unit placement by capturing periodic variations in travel intensity. Consequently, the model becomes responsive not only to infrastructural variables but also to environmental dynamics reflecting human mobility and seasonal patterns, thereby providing a more comprehensive and context-sensitive analytical framework. Effective traffic monitoring in tourist regions can help reduce accident rates. The calculation related to a region's tourism potential is presented in Equation 6.

TUP: The daily number of tourists in the region.

$$T6\ (number\ of\ tourists) = TUP.365 \quad (6)$$

Annual Rain and Snow Levels (T7-Independent Variable) (Gorzelańczyk & Piątkowski, 2024): The levels of rainfall and snowfall in a region can significantly influence the frequency of traffic accidents. Rain and snow make road surfaces slippery, making vehicle control more challenging, reducing driving speeds, and increasing driver reaction times. These factors collectively heighten the risk of accidents. As such, traffic enforcement is critically important during periods of heavy rain and snow. Lowering speed limits, enhancing road safety measures, and alerting drivers play an effective role in reducing accidents. Effective traffic monitoring is crucial for ensuring safety under adverse weather conditions. The calculation related to rain and snow levels is presented in Equation 7.

$YRFL$: Yearly Total Rainfall level (mm), $YSFL$: Yearly Total Snowfall level (mm), $TYRSDD$: Total yearly rainfall and snowfall duration (days)

$$T7\ (fall\ level\ (mm) := \frac{(RFL+SFL)}{365}.TRSDD \quad (7)$$

The variable “fall level (mm)” does not denote the physical height of precipitation but rather represents the total amount of precipitation recorded over a specific time interval (e.g., monthly or annual). This value corresponds to the cumulative precipitation volume measured by meteorological stations and expresses both rainfall and snowfall in terms of their water-equivalent height (mm). Accordingly, the unit “mm” in this context does not refer to the depth of water or snow accumulated on the road surface, but to the total quantity of precipitation falling on a given area. Snowfall is also quantified based on its water equivalent; for instance, 10 mm of snow is considered equivalent to 10 mm of rainfall once melted. This conversion represents a standard and widely accepted procedure in meteorological and hydrometeorological analyses. Therefore, in this study, the “fall level (mm)” variable is employed to represent the total amount of precipitation per unit area, serving as a consistent indicator for comparing different climatic conditions. Both rainfall and snowfall are thus treated not as separate physical heights but as cumulative water-equivalent precipitation values, ensuring methodological consistency and comparability across varying weather conditions.

Annual Frost Events (T8-Independent Variable) (Gorzelańczyk & Piątkowski, 2024): Annual frost events in a region can significantly impact the frequency of traffic accidents. Frost creates slippery road surfaces, complicating driving conditions and increasing braking distances, which elevates the risk of accidents. During winter months, frost events, combined with driver negligence and the use of unsuitable tires, can further increase accident rates. Therefore, traffic enforcement is of paramount importance in regions experiencing annual frost events. Effective traffic monitoring, reinforcement of road safety measures, reduction of speed limits, and raising driver awareness about appropriate behavior under frosty conditions play a critical role in reducing accidents. The calculation related to seasonal frost events is presented in Equation 8.

FED: frost event duration (days) in year,

$AASFED$: Annual average seasonal frost event degree (Celcius).

$$T8\ (degree\ Celsius - day) = FED.|-AASFED\ | \tag{8}$$

The variable T8 represents not only the frequency of frost occurrences but also their intensity, serving as a composite indicator of both duration and severity. The index is calculated by multiplying the number of frost days observed within a specific period by the absolute value of the minimum temperature recorded during those events. This operation captures not just the occurrence of frost, but its thermal intensity, allowing differentiation between short, mild frosts and prolonged, severe freezing periods. Accordingly, T8 does not merely quantify the number of icing days; rather, it functions as a weighted measure of cumulative frost impact, integrating both temporal and thermal dimensions. This makes it a more comprehensive and meaningful variable for modeling frost-related risks that influence infrastructure performance, traffic safety, and surface conditions.

Annual Number of Traffic Penalties (T9-Independent Variable) (Rahimi et al., 2017): The number of traffic penalties issued in a region can influence the frequency of traffic accidents. A high rate of traffic fines encourages drivers to comply with traffic regulations, potentially preventing accidents. Effective enforcement of penalties ensures adherence to speed limits, parking restrictions, and other traffic rules, thereby enhancing road safety. Consequently, traffic enforcement plays a crucial role in this regard. Efficient traffic monitoring, coupled with the fair and consistent implementation of penalties, improves driver behavior and significantly contributes to reducing traffic accidents. The calculation related to T9 is presented in Equation 9.

TP: Annual traffic penalty number

$$T9 = TP\ (number) \tag{9}$$

The variable TP (Annual Traffic Penalty Number) represents the total number of administrative penalties imposed by local traffic enforcement authorities during the specified period, encompassing all types of violations such as speeding, failure to use seat belts, illegal parking, and driving under the influence.

Visibility Distance in Foggy Weather (T10-Independent Variable) (Gorzelańczyk & Piątkowski, 2024): The daily average visibility distance during foggy weather in a region significantly impacts the frequency of traffic accidents. Reduced visibility delays drivers' reactions and makes it more difficult to detect potential hazards, leading to an increased likelihood of accidents. In foggy conditions, drivers need to adjust their speeds and maintain safe following distances, making traffic enforcement particularly crucial under such circumstances. Effective traffic enforcement, including the regulation of speed limits and educating drivers on safe driving practices in foggy weather, plays a critical role in reducing accident risks. The calculation related to T10 is presented in Equation 10.

$AVDFW$: Average visibility distance in foggy weather (m.), *FWD:* Foggy weather duration (number of days)9

$$T10\ (m.) = \left(\frac{1}{AVDFW}\right).FWD \tag{10}$$

As illustrated in Equation T10, the variable represents the annual average of visibility distances measured on foggy days (in meters), while FWD (Foggy Weather Duration) denotes the total number of foggy days observed within the same year (in days).

Accident Rate (TIV): Dependent Variable (Wahi et al., 2018): Several factors play a significant role in the occurrence of traffic accidents in a region, including annual traffic density, total road network, physical characteristics of the road (e.g., inclined road and winding road length, average slope), annual regional population, industrial and commercial activities, tourism potential, annual rainfall and snowfall levels, frost events, annual traffic violation rates, and visibility distance in foggy weather. High traffic density and increasing industrial-commercial activities raise the number of vehicles on the roads, which in turn increases the risk of accidents. The physical features of the road, such as its incline and winding nature, directly affect driving safety. Environmental factors, such as adverse weather conditions, low visibility, and frost events, can cause drivers to lose control. Additionally, high tourist seasons and dense population also contribute to the rise in accident rates. The effective implementation of traffic enforcement, the deterrence effect of traffic fines, and region-specific regulations can help minimize these risks. Evaluating these factors together is crucial for strategic planning aimed at creating safer traffic environments. The TIV formula is presented in Equation 11.

ANA: Annual number of accidents

$$TIV = \frac{ANA}{T2} \quad and \;\; TIV \; standardized \; (Std.) = \frac{\sum_{Year\ 1}^{Year\ n} TIV}{n} \quad n{:}\, Years \; number \tag{11}$$

In line with the aforementioned, the model and dataset relevant to the subject of the research are presented in Table 1.

Table 1. Decision Matrix

REGION A						
Year	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6
T1	8760000	10220000	11315000	16425000	17155000	17885000
T2	4100	4400	4600	4800	5100	5300
T3	4933,52	5223,04	5407,16	5745,75	5831,52	6010,16
T4	9,756098	11,36364	13,04348	14,58333	15,68627	16,98113
T5	10220	11315	12045	12775	14600	15330
T6	5840000	5110000	4380000	4745000	5840000	5110000
T7	122,4986	133,0849	136,7918	142,2466	145,5781	149,7205
T8	90	119	126	136	140	154
T9	1900	2700	3100	3850	4100	4200
T10	1	1,416667	1,583333	2	2,5	4
TIV (Std.)	0,188	0,219	0,242	0,352	0,367	0,383
REGION B						
Year	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6
T1	7665000	9125000	12045000	16060000	16425000	16790000
T2	3100	3800	4200	4500	4700	4900
T3	5506,09	6164,5	6402,5	6717,5	7134,75	7260,8
T4	12,90323	13,15789	14,28571	15,55556	17,02128	18,36735
T5	10950	12045	13870	14600	16425	18250
T6	3285000	3650000	4015000	4380000	4745000	5110000
T7	120,789	148,3041	100,6521	116,0274	158,2192	132,9041
T8	50	60	77	88	91	96
T9	560	642	789	985	996	1100
T10	1	2,6	3,6	4,285714	5	6
TIV (Std.)	0,219	0,242	0,265	0,274	0,285	0,307

3.2. CRITIC Method

The CRITIC method, introduced by Diakoulaki et al. (1995), is a widely adopted Multi-Criteria Decision-Making (MCDM) technique used to objectively determine the relative importance of criteria based on decision alternatives. Its primary advantage lies in incorporating the inter-criterion relationships through Pearson correlation coefficients, ensuring that both conflict and redundancy among criteria are quantitatively reflected in the weighting process (Arslan, 2020). In this approach, the contrast intensity of each criterion derived from its correlation structure is amplified by its standard deviation, allowing for a balanced evaluation of variability and dependence within the decision matrix (Öztel & Alp, 2020; Uludağ & Doğan, 2021; Ulutaş & Topal, 2020). Due to its analytical rigor and objectivity, the CRITIC method has been extensively utilized in the literature for criterion weighting across diverse domains. A summary of recent applications and empirical studies employing this method is presented in Table 2.

Table 2. The CRITIC method in the current literature

Author (s)	Method(s)	Theme
Yılmaz Özekenci (2024)	CRITIC-LOPCOW based COCOSO	Analysis of financial capacity
Mirjalili et al. (2024)	CRITIC	Evaluation of risk assessment in portfolio management
Arshad et al. (2024)	CRITIC based MAIRCA	Assessment of Staff Admissions
Wang (2024)	Pythagorean fuzzy CRITIC-MARCOS	Food suppliers' selection
Khan et al. (2024)	CRITIC based WASPAS	Selection of Sustainable Urban Development Strategies
Rathod et al. (2024)	CRITIC	Analysis of Spatiotemporal Transit Accessibility
Abdullah et al. (2024)	CRITIC-based TOPSIS	Analysis of hybrid renewable energy systems
Das & Behera (2024)	GIS-based AHP, CRITIC and AHP-TOPSIS	Geospatial evaluation of ecological susceptibility
Anjum et al. (2024)	Pythagorean Fuzzy CRITIC-AROMAN	Revolutionary Approaches to Incorporating the Metaverse into Intelligent Transportation Systems
Pajic et al. (2024)	CRITIC-based MOOSRA	Analysis of Cold Chain Monitoring Devices

The procedural steps for applying this method are detailed below in alignment with this concept (Ecer, 2020; Ayçin, 2019)

Cj: $j-th$ evaluation criterion

x_{ij}: value of the $i-th$ alternative according to the $j-th$ evaluation criterion

$x_j^{max.}$: maximum value of the decision alternatives according to the $j-th$ criterion

$x_j^{min.}$: minimum value of the decision alternatives according to the $j-th$ criterion

r_{ij}: value taken by the $i-th$ alternative according to the $j-th$ evaluation criterion

r_{ij}: correlation coefficient between the $j-th$ and $j-th$ criteria

m: alternative number $(i = 1,2,\ldots,m)$

n: Criteria number $(j = 1,2,\ldots n)$

σj: standard deviation of the $j-th$ criterion $(j = 1,2,\ldots,n)$

w_j: weight of the $j-th$ evaluation criterion $(j = 1,2,\ldots,n)$

Step 1: Provision of the decision matrix (X)

$$X = \begin{bmatrix} C_1 & C_2 & \ldots & C_m \\ x_{11} & x_{12} & & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (12)$$

Step 2: Normalization of the decision matrix (r_{ij})

For Benefit-Oriented Criteria:

$$r_{ij} = \frac{x_{ij}-x_j^{min}}{x_j^{maks}-x_j^{min}} \ldots\ldots\ldots j=1,2,\ldots,n \quad (13)$$

For Cost-Oriented Criteria:

$$r_{ij} = \frac{x_j^{maks}-x_{ij}}{x_j^{maks}-x_j^{min}} \ldots\ldots\ldots j=1,2,\ldots,n$$

(14)

Step 3: Construction of the Pearson correlation coefficient matrix (p_{jk})

$$p_{jk}=\frac{\sum_{i=1}^{m}(r_{ij}-\overline{r_j}).(r_{ik}-\overline{r_k})}{\sqrt{\sum_{i=1}^{m}(r_{ij}-\overline{r_j})^2.(r_{ik}-\overline{r_k})^2}}\; j, k=1,2,\ldots,n \quad (15)$$

Step 4: Measurement of the enhanced contrasts of criteria (C_j)

$$\sigma_j=\sqrt{\frac{\sum_{i=1}^{m}(r_{ij}-\overline{r_j})^2}{m-1}} \quad (16)$$

$$C_j=\sigma_j.\sum_{i=1}^{m}\left(1-r_{ij}\right)j=1,2,\ldots,m \quad (17)$$

Step 5: Measurement of criterion weights (degree of importance-w_j)

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

3.3. Curve Estimation

Curve Estimation is a statistical modeling technique designed to identify the mathematical function that best represents the relationship between dependent and independent variables (Torter & Lock, 1993). It serves a crucial role in exploring and analyzing both linear and nonlinear associations within data (Efromovich, 1999). Particularly effective in complex systems where changes in the dependent variable deviate from linearity, this method enhances interpretability and predictive accuracy (Garson, 2012). Depending on data characteristics and the nature of the variable relationship, various functional modelssuch as linear, logarithmic, exponential, polynomial, and power forms may be applied (Karagöz, 2019). These models are systematically presented in the Statistical Package for the Social Sciences (SPSS) framework, as summarized in Table 3.

Table 3. Curve Estimation equations

Model	Equation
Linear	$Y = \beta0 + (\beta1.x)$
Inverse	$Y = \beta0 + (\beta1 /x)$
S-curve	$Y = e^{(\beta0 + (\beta1/x))}$ or $\ln(Y) = \beta0 + (\beta1/x)$
Logarithmic	$Y = \beta0 + (\beta1 \ln(x))$
Quadratic	$Y = \beta0 + (\beta1x) + (\beta2x^2)$
Cubic	$Y = \beta0 + (\beta1\, x) + (\beta2x^2) + (\beta3x^3)$
Power	$Y = \beta0\ (x^{\beta1})$ or $\ln(Y) = \ln(\beta0) + (\beta1\ln(x))$
Compound	$Y = \beta0\ (\beta1^x)$ or $\ln(Y) = \ln(\beta0) + (\ln(\beta1)x)$
Growth	$Y = e^{(\beta0 + (\beta1 * x))}$ or $\ln(Y) = \beta0 + (\beta1\, x)$
Exponential	$Y = \beta0 * (e^{(\beta1\, x)})$ or $\ln(Y) = \ln(\beta0) + (\beta1x)$
Logistic	$Y = \ln(\beta0) + (\ln(\beta1)x)$

Reference: IBM Corp., 2013

According to Table 3 (In this prediction equation), Y represents the TIV amount. $\beta0$ denotes the Y -intercept, while $\beta1$ indicates the rate of change in $T0$ increase in the independent variable. $\beta2$ is the regression coefficient associated with the squared term of the independent variable, and $\beta2$ corresponds to the regression coefficient for the cubic term of the independent variable. The independent variable, denoted as x refers to the independent traffic variables while x^2 and x^3 represent the square and cube of TIV, respectively. Additionally, In stands for the natural logarithm. $\beta1$, $\beta2$, $\beta3$, $\beta4$, βz quantify the contributions of the respective independent variables x, x^2 and x^3 and any additional predictors x_k to the model (Abdallah & Gauda, 2024). An example representation of the curve estimation functions shown in Table 3 is presented in Figure 1.

The Curve Estimation process begins with identifying potential relationships between dependent and independent variables, followed by selecting the most appropriate functional form based on data characteristics and estimating its parameters. The model with the highest significance level or, when equal, the highest coefficient of determination is preferred (Karagöz, 2016). This approach enables modeling of complex and realistic structures beyond the constraints of linear models, provided that theoretical coherence and data suitability are maintained (Karagöz, 2017).

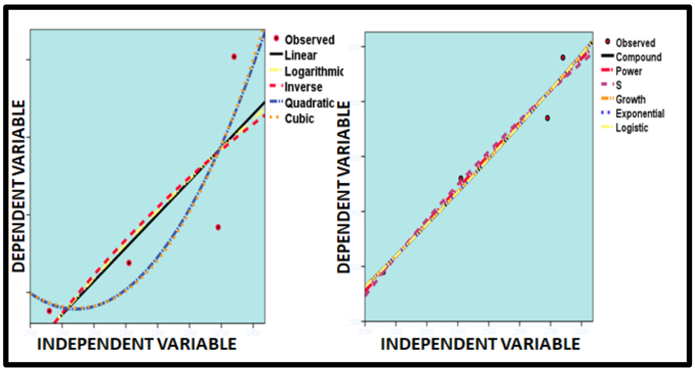

Figure 1. Curve Estimation Models

Curve Estimation has been effectively utilized in diverse fields. Jafri et al. (2011) applied it with the Cobb–Douglas model to predict sugar production, while Marti-Puig et al. (2014) found a cubic model best described tobacco leaf drying dynamics. Baghdadi and Pani (2012) improved dental age prediction through population-specific curves. Jomnonkwao et al. (2020) used it for traffic forecasting in Thailand, and Zhang et al. (2021) demonstrated its engineering relevance in bearing performance modeling. Recent studies have further expanded its applications: Castro et al. (2024) linked idiopathic dizziness mechanisms to postural control, Chhillar et al. (2024) validated a digital financial literacy model, Li et al. (2024) identified a quadratic link between inflammatory markers and vitamin D metabolites, Lu and Gao (2021) developed urban fuel-consumption models, and Zhang et al. (2024) examined eutrophication–oxidation potential interactions. Collectively, these studies highlight Curve Estimation as a versatile and scientifically robust tool for exploring and quantifying nonlinear relationships across disciplines.

3.4. Proposed Method: (Critic-Based Curve Estimations-CBCE)

The proposed CBCE method models the influence of independent traffic criteria on the dependent variable accident rate using eleven functional forms defined in SPSS literature. In line with standard statistical conventions, the optimal model is determined by selecting the function with the lowest p-value, indicating the highest level of significance. When multiple models exhibit identical significance, the one with the highest coefficient of determination *(R^2)* is chosen as the best fit.

Following model selection, the first derivative of each function is computed to evaluate whether the relationship between the variables aligns with expected traffic accident behavior, identifying increasing or decreasing trends in relation to independent variable changes. To quantify the overall effect of these variables on accident rate (TIV), definite integrals are then calculated, allowing assessment of the total impact across specific intervals. This dual analytical approach enables simultaneous mathematical and statistical evaluation, ensuring accurate determination of the optimal distribution of traffic control units across regions. Prior to implementation, criterion weights are derived using the CRITIC method, which calculates weights based on inter-criterion correlations and contrast intensity (Ecer, 2020). Recognized for its robustness and reliability, CRITIC complements the CBCE approach, as both emphasize the structural relationships among variables. This methodological coherence where independent and dependent relationships are central justifies the integration of CRITIC for weight computation within the CBCE framework (Ayçin, 2019; Ecer, 2020).

Cj: $j-th$ evaluation criterion

x_{ij}: Value of the $i-th$ alternative according to the $j-th$ evaluation criterion

w_j: Weight of the $j-th$ evaluation criterion ($j = 1, 2, \dots, n$)

m: Alternative number (Year) ($i = 1,2, \dots, m$)

n: Criteria number (Independent Variable) ($j = 1,2, \dots, n$)

k: Criteria number (Dependent Variable) ($j = 1,2, \dots, k$)

X: Decision matrix

WDM: Weighting of decision matrix

SS_{ij}: Standardized Scores of $i-th$ alternative according to the $j-th$ evaluation criterion

$p_{f(x)\rightarrow min.}$: with the lowest p-value (highest significance level)

ES_{Tj}: Effect score of independent variables

TES_j: Total effect score of independent variables

DR: Distribution Rate

Step 1: Generating the decision matrix (X)

The decision matrix is created by performing the relevant calculations from Equation 1 to Equation 11 for the regions. In this regard, the decision matrix is standardized using Equation 19.

$$X = \begin{bmatrix} C_1 & C_2 & \dots & C_m \\ x_{11} & x_{12} & & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad (19)$$

Step 2: Weighting of decision matrix (WDM)

In the second stage, the decision matrix is weighted using Equation 20. During this weighting process, the criteria weights of the 10 independent traffic variables measured previously by the CRITIC method are calculated by considering the mathematical operations from Equation 12 to Equation 18. Subsequently, each value in the decision matrix is multiplied by the corresponding criterion weight to create the weighted decision matrix, as shown in Equation 21. The equations for the weighted decision matrix are presented below.

$$WDM_{ij} = x_{ij}.w_j \quad (20)$$

$$WDM = \begin{bmatrix} C_1 & C_2 & \dots & C_m \\ WDM_{11} & WDM_{12} & & WDM_{1n} \\ WDM_{21} & WDM_{22} & \cdots & WDM_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ WDM_{m1} & WDM_{m2} & \cdots & WDM_{mn} \end{bmatrix}$$
(21)

Step 3: Measurement of standardized scores (SS_{ij})

In this step, the values of the weighted decision matrix created in the second step are standardized between 0 and 1 using Equation 22.

$$SS_{ij} = \frac{WDM_i}{\sum_{i=1}^{m} WDM_i} \tag{22}$$

Step 4: Selection of optimal curve function

In this step, the function that best explains the relationship between the independent variables and the dependent variable is selected from the 11 different functions found in the SPSS literature. As previously explained, when selecting the function, the one with the highest significance value in explaining the relationship between the independent variables and the dependent variables was preferred. The function selection process is shown in Equation 23.

$$Preferred\ function = p_{f(x)\to min.} \tag{23}$$

Step 5: The compatibility of the equations with the theory

In this step, if the relationship between the independent variable and the dependent variable is of a direct proportionality, the function that reflects the relationship between the dependent and independent variables is used. On the other hand, if the relationship between the independent and dependent variables is inverse, the function reflecting the relationship between them is considered a decreasing function. In this regard, if the derivative of the function is greater than 0, the function is increasing (direct), while if the derivative is less than 0, the function is decreasing (inverse). If the function is not compatible with the theory, the function or functions reflecting the relationship or relationships are excluded from the calculation process. The equations related to the relationship between the independent and dependent variables and their compatibility with the theory are explained below. If the relationship between the dependent and independent variables is consistent with the theory in the same direction, Equation 24 is used; if it is inverse, Equation 25 is used.

$$p < .05, f(x)' > 0 \tag{24}$$

$$p < .05, f(x)' < 0 \tag{25}$$

Step 5: Calculation of the effect score of independent variables on the dependent variable (ES_{Tj})

In this step, the total change of the dependent variable in the range of the standardized values of the independent variables is determined through interval integration. Thus, the effects of the standardized values of the independent variables on the standardised dependent variable are explained in Equations 26, 27, 28, and 29.

$$ES_{T1\to TIV_1} = \int_{SS_{T1-min.}}^{SS_{T1-max.}} f(x)\,dx \tag{26}$$

$$ES_{T2\to TIV_1} = \int_{SS_{T2-min.}}^{SS_{T2-max.}} f(x)\,dx \tag{27}$$

… … …

… … …

… … …

$$ES_{Tn\to TIV_1} = \int_{SS_{Tn-min.}}^{SS_{Tn-max.}} f(x)\,dx \tag{28}$$

… … …

… … …

… … …

$$ES_{T(n-1)\to TIV_k} = \int_{SS_{T(n-1)-min.}}^{SS_{T(n-1)-max.}} f(x)\,dx \tag{29}$$

$$ES_{Tn\to TIV_k} = \int_{SS_{Tn-min.}}^{SS_{Tn-max.}} f(x)\,dx \tag{30}$$

Step 7: Calculation of the total effect score of independent variables on the dependent variable (TES_j)

$$TES_j = \sum_{j=1,\ k=1}^{n} \left(ES_{Tj-TIV_1}\right) + \sum_{j=1,\ k=1}^{n} \left(ES_{Tj-TIV_2}\right) + \dots\dots\dots + \sum_{j=1,\ k=1}^{n} \left(ES_{Tn-TIV_k}\right) \tag{31}$$

Step 8 Calculation of Distribution Rate (DR)

$$DR = \frac{TES_j}{\sum_{J=1}^{n} TES_j} \tag{32}$$

The CBCE method provides an integrated mathematical and statistical framework for analyzing the influence of independent variables on a dependent variable through derivative and integral analyses. Derivative analysis identifies whether a function exhibits an increasing or decreasing trend, while integral computation quantifies the cumulative effect of changes in independent variables on the dependent variable. This dual approach enables both static and dynamic assessments, offering a deeper and more precise understanding of variable interactions. The conceptual and mathematical structure of the proposed model is illustrated in Figure 2.

4. Results

4.1. Computational Analysis

In the study, traffic criterion weight coefficients for each of Regions A and B were calculated using the equations defined in the CRITIC method. Accordingly, the traffic criterion weight coefficients calculated via the CRITIC method based on the traffic criterion values of each region, as well as the rankings of these weight coefficients, are presented in Table 4.

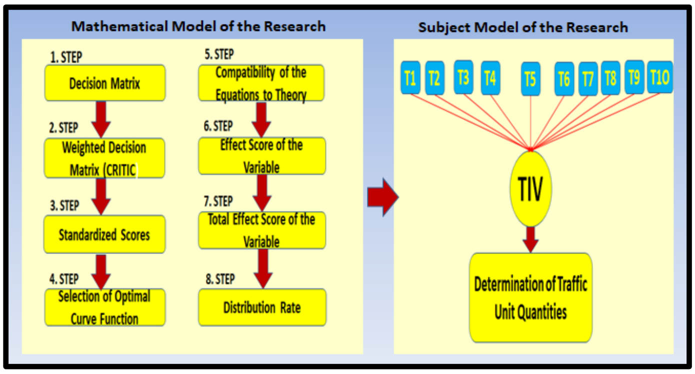

Figure 2. CRITIC-based Curve Estimation models (source: IBM Corp., 2013)

Table 4. CRITIC Scores

Variable (Criteria)	Region A	Rank	Region B	Rank
T1	0,074	2	0,075	3
T2	0,055	8	0,059	9
T3	0,054	9	0,059	8
T4	0,056	6	0,071	4
T5	0,057	4	0,062	6
T6	0,482	1	0,060	7
T7	0,056	7	0,199	2
T8	0,058	3	0,066	5
T9	0,056	5	0,295	1
T10	0,051	10	0,057	10

In the second stage of the study, the decision matrix was constructed using the proposed method based on Equation 19 for the independent variables. The values of the decision matrix in question were previously presented in Table 1. In the second step of the method, only the weighted values of the independent variables were calculated using Equations 20 and 21. The calculated weighted values are provided in Table 5.

In the third step of the method, the dependent and independent values are standardized using Equation 22. The standardized values are presented in Table 6.

In the fourth step, the impact values of the independent traffic criteria on the dependent traffic criteria, based on the standardized values, were determined using SPSS within the scope of Curve Estimation and Equation 23 to identify the most significant regression function. Subsequently, the theoretical compatibility structure between the dependent and independent variable criterion values was determined using Equations 24 and 25. Accordingly, for each region, the most significant functions representing the relationship between the independent traffic criteria and the dependent criterion values, as well as the theoretical compatibility of these functions, are presented in Tables 7 and 8. As previously noted, increases in T1–T8 and T10 are theoretically expected to elevate accident rates (directly proportional), whereas an increase in T9 should reduce them (inversely proportional). However, as shown in Table 7, the analysis for Region A revealed that T6 exhibited an inverse association with the dependent variable (TIV), while all other independent variables displayed direct relationships. Among these, T6 demonstrated significance levels exceeding 0.05, with the exponential function showing the closest value to the significance threshold. Hence, the relationship between T6 and TIV was deemed statistically insignificant and inconsistent with established traffic theory.

Table 5. Weighted scores

REGION A							
Criteria	w	Year1	Year2	Year3	Year4	Year5	Year6
T1	0,074	646001,3	753668,2	834418,3	1211252	1265086	1318919
T2	0,055	227,3823	244,02	255,1118	266,2036	282,8414	293,9332
T3	0,054	267,7623	283,4757	293,4686	311,8453	316,5004	326,1959
T4	0,056	0,549645	0,640212	0,734852	0,821605	0,883743	0,956694
T5	0,057	584,0364	646,6118	688,3286	730,0455	834,3377	876,0546
T6	0,482	2813306	2461643	2109979	2285811	2813306	2461643
T7	0,056	6,805643	7,393785	7,599726	7,902778	8,087866	8,318009
T8	0,058	5,255747	6,949266	7,358046	7,942018	8,175607	8,993167
T9	0,056	107,2568	152,4176	174,9979	217,3362	231,4489	237,094
T10	0,051	0,050902	0,072111	0,080595	0,101804	0,127255	0,203607
REGION B							
Criteria	w	Year1	Year2	Year3	Year4	Year5	Year6
T1	0,075	572267	681270,3	899276,8	1199036	1226287	1253537
T2	0,059	181,639	222,6543	246,0916	263,6696	275,3882	287,1068
T3	0,059	324,387	363,1767	377,1983	395,7563	420,3383	427,7644
T4	0,071	0,913546	0,931577	1,011426	1,101331	1,205103	1,300405
T5	0,062	675,8122	743,3934	856,0288	901,0829	1013,718	1126,354
T6	0,060	195903,2	217670,2	239437,2	261204,3	282971,3	304738,3
T7	0,199	23,97852	29,44069	19,98101	23,03326	31,40899	26,38355
T8	0,066	3,297446	3,956935	5,078067	5,803505	6,001352	6,331097
T9	0,295	164,9588	189,1134	232,4151	290,1507	293,391	324,0262
T10	0,057	0,056645	0,147278	0,203924	0,242766	0,283227	0,339873

Table 6. Standardized scores

REGION A						
Criteria	Year1	Year2	Year3	Year4	Year5	Year6
T1	0,188	0,219	0,242	0,352	0,367	0,383
T2	0,229	0,246	0,257	0,268	0,285	0,296
T3	0,232	0,245	0,254	0,270	0,274	0,282
T4	0,200	0,233	0,268	0,299	0,322	0,348
T5	0,220	0,244	0,260	0,276	0,315	0,331
T6	0,291	0,255	0,218	0,236	0,291	0,255
T7	0,229	0,249	0,256	0,266	0,272	0,280
T8	0,191	0,253	0,268	0,289	0,297	0,327
T9	0,165	0,234	0,268	0,333	0,355	0,364
T10	0,167	0,236	0,264	0,333	0,417	0,667
TIV (Std.)	0,188	0,219	0,242	0,352	0,367	0,383
REGION B						
Criteria	Year1	Year2	Year3	Year4	Year5	Year6
T1	0,098	0,117	0,154	0,206	0,210	0,215
T2	0,123	0,151	0,167	0,179	0,187	0,194
T3	0,141	0,157	0,163	0,171	0,182	0,185
T4	0,141	0,144	0,156	0,170	0,186	0,201
T5	0,127	0,140	0,161	0,169	0,191	0,212
T6	0,130	0,145	0,159	0,174	0,188	0,203
T7	0,155	0,191	0,130	0,149	0,204	0,171
T8	0,108	0,130	0,167	0,190	0,197	0,208
T9	0,110	0,127	0,156	0,194	0,196	0,217
T10	0,044	0,116	0,160	0,191	0,222	0,267
TIV (Std.)	0,219	0,242	0,265	0,274	0,285	0,307

Table 7. Functions that arise between the dependent variable and the independent variables (Curve Estimation) REGION A

C.	F	Function $f(x)$	Deriviate $f(x)'$	Inc. or Dec.	CCT
T1	S	$e^{(-0.56-0.2/x)}$	$\frac{d}{dx}\left(e^{(-0.56-0.2/x)}\right)=\frac{e^{-0.56-\frac{1}{5x}}}{5x^2}, f(x)'>0$	Inc.	+
T2	L	$2.45x-0.364$	$\frac{d}{dx}(2.45x-0.364)=2{,}45, f(x)'>0$	Inc.	+
T3	Lo	$1.39+0.819\log(x)$	$\frac{d}{dx}(1.39+0.819\log(x))=\frac{819\log(e)}{1000x}$, $f(x)'<0$	Inc.	+
T4	Cu	$-0.08+1.41x$ $-1.31x^3$	$\frac{d}{dx}(-0.08+1.41x-1.31x^3)=\frac{141-393x^2}{100}$, $f(x)'>0$	Inc.	+
T5	I	0.674-(0.106/x)	$\frac{d}{dx}\left(0.674-(\frac{0.106}{x})\right)=\frac{53}{500x^2}, f(x)'>0$	Inc.	+
T6	E	$0.450e^{-1.923x}$ $(p>.05)$	$\frac{d}{dx}(0.450e^{-1.923x})=-\frac{17307e^{-\frac{1923x}{1000}}}{20000}, f(x)'<0$	Dec.	-
T7	E	$0.011\mathbf{e}^{(12.43)x}$	$\frac{d}{dx}(0.011\mathbf{e}^{12.43x})=\frac{13673e^{\frac{1243x}{100}}}{100000}, f(x)'<0$	Dec.	+
T8	E	$0.076\,\boldsymbol{e}^{(4.759)x}$	$\frac{d}{dx}\left(0.076\,\mathbf{e}^{(4.759)x}\right)=\frac{90421e^{\frac{4759x}{1000}}}{250000}, f(x)'>0$	Inc.	+
T9	E	$0.12\,e^{(2.91)x}$	$\frac{d}{dx}0.12\,e^{(2.91)x}=\frac{873\mathbf{e}^{\frac{291x}{100}}}{2500}, f(x)'>0$	Inc.	-
T10	I	$0.413-(0.038/x)$	$\frac{d}{dx}(0.413-(0.038/x)=\frac{19}{500x^2}, f(x)'>0$	Inc.	+

Note: C.: Criteria, F: Function type, I: Inverse S: S-Curve, L: Linear, Cu: Cubic, E: Exponential, Inc.: Increasing function, Dec.: Decreasing function, CCT: Compliance condition to traffic theory, +: Compliance, -: Not compliance.

Table 8. Functions that arise between the dependent variable and the independent variables (Curve Estimation) REGION B

C.	F	Function	Derviate	Inc. or Dec.	CCT
T1	S	$e^{(-1.005-0.05/x)}$	$\frac{d}{dx}e^{(-1.005-0.05/x)}=\frac{e^{-1.005-\frac{1}{20x}}}{20x^2}, f(x)'>0$	Inc.	+
T2	Cu.	$0.202-1.494x^2$ $+21.4x^3$	$\frac{d}{dx}(0.202-1.494x^2+21.4x^3)=\frac{873e^{\frac{291x}{100}}}{2500}, f(x)'>0$	Inc.	+
T3	E	$2.15x^{1.168}$	$\frac{d}{dx}(2.15x^{1.168})=\frac{3139x^{0.168}}{1250}, f(x)'>0$	Inc.	+
T4	I	$0.482-(0.035/x)$	$\frac{d}{dx}((0.482-(0.035/x))=\frac{7}{200x^2}, f(x)'>0$	Inc.	+
T5	I	$0.429-(0.026/x))$	$\frac{d}{dx}(0.429-(0.026/x))=\frac{13}{500x^2}, f(x)'>0$	Inc.	+
T6	S	$e^{-0.619-(0.116/x)}$	$\frac{d}{dx}\left(e^{-0.619-(0.116/x)}\right)=\frac{29e^{-0.619-\frac{29}{250x}}}{250x^2}, f(x)'>0$	Inc.	+
T7	L	$0.197x+0.233$ $(p>.05)$	$\frac{d}{dx}(0.197x+0.233)=0.197, f(x)'>0$	Inc.	-
T8	L	$0.161e^{2.96x}$	$\frac{d}{dx}(0.161e^{2.96x})=\frac{5957\boldsymbol{e}^{\frac{74x}{25}}}{12500}, f(x)'>0$	Inc.	+
T9	S	$e^{(-0.912+-0.066/x)}$	$\frac{d}{dx}\left(e^{(-0.912+-0.066/x)}\right)=\frac{33e^{-0.912-\frac{33}{500x}}}{500x^2}, f(x)'>0$	Inc.	-
T10	L	$0.205e^{1.517x}$	$\frac{d}{dx}(0.205e^{1.517x})=\frac{62197\boldsymbol{e}^{\frac{1517x}{1000}}}{200000}, f(x)'>0$	Inc.	+

Note: C.: Criteria, F: Function type, I: Inverse S: S-Curve, L: Linear, Cu: Cubic, E: Exponential, Inc.: Increasing function, Dec.: Decreasing function, CCT: Compliance condition to traffic theory, +: Compliance, -: Not compliance.

Similarly, for Region B, all independent variables except T7 exhibited statistically significant direct relationships with TIV (Table 7). Yet, when Tables 7 and 8 were evaluated together, T9 showed a positive rather than the theoretically expected negative association with TIV in both regions, indicating a deviation from theoretical expectations.

In the fifth analytical stage, the total variation in the dependent variable attributable to changes in the independent variables was quantified using the definite integral method defined in Equation 10. This calculation, based on the smallest and largest standardized values of each independent variable, provided a precise measure of the overall influence of independent traffic criteria on accident rate dynamics.

A REGION

$T1 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.188}^{0.352} e^{(-0.56 - 0.2/x)} = -\frac{e^{-\frac{14}{25}}\left(47\int_1^\infty \frac{e^{\frac{-50t}{47}}}{t^2}dt - 88\int_1^\infty \frac{e^{\frac{-25t}{44}}}{t^2}dt\right)}{250} = 0{,}044$$

$T2 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.229}^{0.268} 2.45x - 0.364dx = \frac{381927}{40000000} = 0{,}010$$

$T3 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.232}^{0.27} 1.39 + 0.819\log(x)dx = \log(\boldsymbol{e})\left(\frac{22113\ln(0.27)}{100000} - \frac{23751\ln(0.232)}{125000} - 0.031\right) + 0.053 = 0{,}034$$

$T4 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.2}^{0.299} 0.401 - \frac{0.037}{x}dx = -\frac{37\ln(0.299)}{1000} - \frac{37\ln(5)}{1000} + 0.039699 = 0.025$$

$T5 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.22}^{0.276} 0.674 - \frac{0.106}{x}dx = \frac{53\ln(0.22)}{500} - \frac{53\ln(0.276)}{500} + 0.0377 = 0{,}014$$

$T6 \rightarrow TIV$: Not Compliance with the traffic theory ($p > .05$)

$$\int_{0.218}^{0.291} 0.45\boldsymbol{e}^{(-1.923)x}dx = \frac{150}{641\boldsymbol{e}^{0.419214}} - \frac{150}{641\boldsymbol{e}^{0.559593}} = 0{,}020$$

$T7 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.229}^{0.266} 0.011\boldsymbol{e}^{(12.43)x}dx = \frac{\boldsymbol{e}^{3.31} - \boldsymbol{e}^{2.85}}{1130} = 0{,}009$$

$T8 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.191}^{0.289} 0.076\boldsymbol{e}^{(4.759)x}dx = \frac{76\boldsymbol{e}^{1.375351} - 76\boldsymbol{e}^{0.908969}}{4759} = 0{,}024$$

$T9 \rightarrow TIV$: Not compliance with the traffic theory

$$\int_{0.165}^{0.333} 0.12\boldsymbol{e}^{(2.91)x}dx = \frac{4\boldsymbol{e}^{0.96903} - 4\boldsymbol{e}^{0.48015}}{97} = 0{,}042$$

$T10 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.167}^{0.333} 0.413 - \left(\frac{0.038}{x}\right)dx = \frac{19\ln(0.167)}{500} - \frac{19\ln(0.333)}{500} + 0.069 = 0{,}042$$

B REGION

$T1 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.098}^{0.206} \boldsymbol{e}^{-1.005-\frac{0.05}{x}}dx = -\frac{e^{-\frac{201}{200}}\left(49\int_1^\infty \frac{e^{\frac{-25t}{49}}}{t^2}dt - 103\int_1^\infty \frac{e^{\frac{-25t}{103}}}{t^2}dt\right)}{500} = 0{,}044$$

$T2 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.123}^{0.179} 0.202 - 1.494xx + 21.4xxxdx = \frac{1706302101}{125000000000} = 0{,}014$$

$T3 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.141}^{0.171} 2.15x^{1.168}dx = \frac{1075(0.171)^{2.168} - 1075(0.141)^{2.168}}{1084} = 0{,}007$$

$T4 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.141}^{0.17} 0.482 - \left(\frac{0.035}{x}\right) dx = \frac{7\ln(0.141)}{200} - \frac{7\ln(0.17)}{200} + 0.014 = 0{,}007$$

$T5 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.127}^{0.169} 0.429 - \left(\frac{0.026}{x}\right) dx = \frac{13\ln(0.127)}{500} - \frac{13\ln(0.169)}{500} + 0.018018 = 0{,}011$$

$T6 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.130}^{0.174} \boldsymbol{e}^{-0.619-\frac{0.116}{x}}dx = -\frac{e^{-\frac{619}{1000}}\left(65\int_1^{\infty}\frac{e^{\frac{-58t}{65}}}{t^2}dt - 87\int_1^{\infty}\frac{e^{\frac{-2t}{3}}}{t^2}dt\right)}{500} = 0{,}011$$

$T7 \rightarrow TIV$: Not Compliance with the traffic theory $(p > .05)$

$$\int_{0.13}^{0.191} 0.197x + 0.233dx = \frac{32283457}{2000000000} = 0{,}016$$

$T8 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.108}^{0.19} 0.161\boldsymbol{e}^{2.96x}dx = \frac{161\boldsymbol{e}^{0.5624} - 161\boldsymbol{e}^{0.31968}}{2960} = 0{,}021$$

$T9 \rightarrow TIV$: Not compliance with the traffic theory

$$\int_{0.110}^{0.194} \boldsymbol{e}^{-0.619-\frac{0.116}{x}}dx = -\frac{e^{-\frac{114}{225}}\left(55\int_1^{\infty}\frac{e^{\frac{-3t}{5}}}{t^2}dt - 97\int_1^{\infty}\frac{e^{\frac{-33t}{97}}}{t^2}dt\right)}{500} = 0{,}022$$

$T10 \rightarrow TIV$: Compliance with the traffic theory

$$\int_{0.044}^{0.191} 0.205\boldsymbol{e}^{1.517}xdx = \frac{283269\boldsymbol{e}^{1.517}}{80000000} = 0.016$$

In the 6th step of the method, the effects of theory-compliant independent variables on the dependent variable, the accident rate, were calculated for each region using the functions described in Equations 26, 27, 28, 29 and 30. Subsequently, in the seventh step, the total effects of the independent traffic criteria were measured using Equation 31. In the final step, the levels of traffic enforcement determination were evaluated using Equation 32. The calculated values are presented in Table 9.

Table 9. Total effect scores and distribution ratios

Criteria	Total Effect Scores		Distribution Ratios	
	A Region	B Region	A Region	B Region
T1	0,044	0,044		
T2	0,010	0,014		
T3	0,034	0,007		
T4	0,025	0,007		
T5	0,014	0,011		
T6	-----	0,011	53%	47%
T7	0,009	-----		
T8	0,024	0,021		
T9	-----	0,048		
T10	0,042	0,016		
Sum	0,202	0,179		

Table 9 comprehensively presents the total effect scores of traffic criteria for Regions A and B, along with the distribution ratios of these scores between the two regions. The impact of each criterion on the dependent variable was calculated separately for both Region A and Region B, and the distribution ratios were determined by considering all T criteria. According to the table, the total effect scores for Regions A and B were calculated as 0.202 and 0.179, respectively. These totals were used to calculate the distribution ratios, which were determined to be 53% for Region A and 47% for Region B. Upon examining Table 9, it was observed that some criteria had no effect in certain regions. For instance, the T6 criterion had no impact in Region A but was calculated as 0.011 in Region B. Similarly, the T7 criterion was ineffective in Region B but had a total effect score of 0.009 in Region A. In summary, this approach allows for a comparative analysis of the effects between the two regions and facilitates the examination of the regional contributions of each criterion to the total effect.

4.2. Sensitivity Analysis

A method used to evaluate the robustness of MCDM approaches involves adding new alternatives to the original set or removing criteria starting from the least significant one (the weakest criterion). In such scenarios, an MCDM method should demonstrate stability and avoid significant changes in the ranking of alternatives (Demir & Arslan, 2022). Similar to this approach, the sensitivity level of the model was measured by removing criteria starting from the weakest independent variable and assessing the theoretical compatibility of the criteria based on their effects on the dependent variable. This is because, in this method, when each independent variable is removed from the dataset, the weight values will change according to the CRITIC method. Calculations revealed that, after the removal of each independent variable, different functions were formed for certain criteria in terms of how the independent variables influenced the dependent variable. However, as reflected in the findings, all the functions maintained their theoretical compatibility. Accordingly, based on scenarios generated by starting from the weakest independent variable (the independent criterion with the lowest quantitative impact value), the rankings of the effects of independent variables on the dependent variable are presented in Table 10. A visual representation of these rankings is illustrated in Figure 3.

When Table 10 and Figure 3 are evaluated together, it is observed that in the rankings of influence values after the removal of each independent traffic variable, changes occurred in the rankings for scenarios S1 and S2 in Region A. Similarly, in Region B, ranking changes were noted in Scenarios S1, S2, and S3. However, when assessed holistically, it was observed that there were no significant changes in the overall rankings. Therefore, based on this outcome, the proposed method (CBCEM) is evaluated to possess an ideal level of sensitivity.

Table 10. Rank reversal of criteria

A REGION										
C.	SO	S1	S2	S3	S4	S5	S6	S7	S8	S9
T10	10									
T9	9	9 (L)								
T5	8	7 (S)	8 (Lo)							
T6	7	8 (Lo)	7 (Q)	7 (L)						
T3	6	6 (I)	6 (I)	6 (Cu)	6 (I)					
T8	5	5 (E)	5 (P)	5 (Q)	5 (P)	4 (P)				
T4	4	4 (P)	4 (C)	4 (E)	4 (E)	5 (C)	4 (E)			
T2	3	3 (E)	3 (S)	3 (I)	3 (I)	3 (Lo)	3 (L)	3 (Q)		
T7	2	2 (Cu)	2 (L)	2 (S)	2 (L)	2 (E)	2 (P)	2 (E)	2 (I)	
T1	1	1 (L)	1 (L)	1 (L)	1 (L)	1 (L)	1 (L)	1 (L)	1 (L)	1
B REGION										
C.	SO	S1	S2	S3	S4	S5	S6	S7	S8	S9
T7	10									
T4	9	9 (L)								
T2	8	8 (Q)	8 (E)							
T6	7	7 (L)	7 (I)	7 (L)						
T8	6	6 (S)	5 (Lo)	6 (C)	6 (S)					
T5	5	5 (Q)	6 (S)	5 (E)	5 (L)	5 (S)				
T3	4	4 (I)	4 (Q)	4 (Cu)	4 (P)	4 (E)	4 (E)			
T10	3	2 (Lo)	3 (L)	3 (S)	3 (I)	3 (C)	3 (Lo)	3 (I)		
T1	2	3 (S)	2 (P)	1 (L)	2 (E)	2 (L)	2 (Q)	2 (E)	2 (S)	
T9	1	1 (L)	1 (E)	2 (E)	1 (S)	1 (E)	1 (E)	1 (L)	1 (L)	1

Note: I: Inverse function, S: S-Curve function, L: Linear function, C: Compound function, E: Exponential function, Q: Quadratic function, E: Exponential function, P: Power function, Cu: Cubic Function, Lo: Logarithmic function, I: Inverse

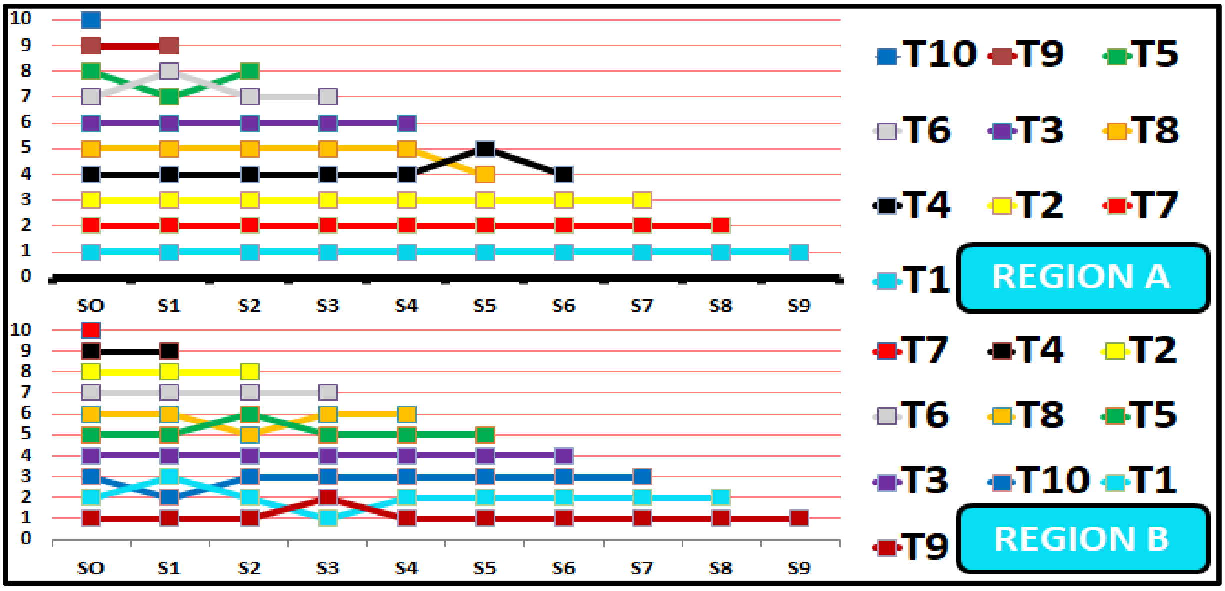

Figure 3. Rank reversal visual

4.3. Comperative Analysis

The comparative analysis evaluates the consistency, reliability, and ranking performance of the proposed method against established analytical approaches. Its primary objective is to validate the accuracy and robustness of the proposed framework while demonstrating statistically meaningful alignment with existing methodologies (Keshavarz-Ghorabaee et al., 2021). Given that the proposed method quantifies the influence of independent variables on a dependent variable, these effects were assessed using Somer's D association coefficient, canonical correlation analysis, and Structural Equation Modeling (SEM) within the standardized data structure defined in Equation 23. These methods were selected for their proven stability and robustness in determining variable interdependencies (Karagöz, 2019). In all three comparative techniques, effect coefficients may assume negative values when an independent variable exerts an inverse influence on the dependent variable (Karagöz, 2017). However, in the proposed model, the total variation explained by independent variables is always expressed as a positive value, while negative impacts are identified through the first derivative of the function obtained via Curve Estimation, where a derivative less than zero signifies a decreasing trend. Accordingly, the comparative evaluation focuses not on the absolute magnitude of effect coefficients from other methods but on the directional consistency (positive or negative) of variable relationships. The increasing or decreasing functional trends derived from the proposed method, as reported in Tables 7 and 8, were examined for agreement with the directional outcomes obtained from other techniques. The comparative results summarizing these directional correspondences between the proposed method and alternative approaches are presented in Table 11.

When the functional models in Tables 7 and 8 are evaluated alongside the statistical results in Table 11, it becomes evident that the relationships between the dependent and independent variables have been modeled with both theoretical and statistical coherence, thereby enhancing the validity and explanatory strength of the framework.

The directional responses of the dependent variables to changes in the independent variables whether increasing or decreasing correspond precisely to the derivatives of the identified functions, reflecting consistency with the physical and theoretical nature of the variables. This confirms the mathematical soundness of the proposed model. While minor variations exist between Regions A and B, these are attributable to localized dynamics, underscoring the model's sensitivity and adaptability to regional characteristics.

Moreover, the alignment of the functional relationships with the results obtained from Somer's D coefficient, canonical correlation, and SEM analyses (Table 11) provides robust empirical support for the model. These complementary statistical approaches verify that the relationships are both directionally and quantitatively significant, reinforcing the model's reliability.

Table 11. The other method's score

C.	Somer's D Coefficient		Structural Equation Modeling		Canonical Correlation	
A REGION						
	Score	Compliance Condition	Score	Compliance Condition	Score	Compliance Condition
T1	0,413	Compliance	0,485	Compliance	0,322	Compliance
T2	0,328	Compliance	0,492	Compliance	0,467	Compliance
T3	0,545	Compliance	0,629	Compliance	0,599	Compliance
T4	0,802	Compliance	0,719	Compliance	0,498	Compliance
T5	0,529	Compliance	0,628	Compliance	0,412	Compliance
T6	-0,513	Compliance	-0,489	Compliance	-0,534	Compliance
T7	0,712	Compliance	0,612	Compliance	0,495	Compliance
T8	0,734	Compliance	0,589	Compliance	0,523	Compliance
T9	0,623	Compliance	0,567	Compliance	0,534	Compliance
T10	0,595	Compliance	0,699	Compliance	0,499	Compliance
B REGION						
C.	Somer's D Coefficient		Structural Equation Modeling		Canonical Correlation	
	Score	Compliance Condition	Score	Compliance Condition	Score	Compliance Condition
T1	0,444	Compliance	0,403	Compliance	0,481	Compliance
T2	0,417	Compliance	0,466	Compliance	0,517	Compliance
T3	0,347	Compliance	0,564	Compliance	0,599	Compliance
T4	0,693	Compliance	0,421	Compliance	0,674	Compliance
T5	0,739	Compliance	0,682	Compliance	0,402	Compliance
T6	0,518	Compliance	0,426	Compliance	-0,367	Compliance
T7	0,608	Compliance	0,501	Compliance	-0,403	Compliance
T8	0,615	Compliance	0,505	Compliance	0,444	Compliance
T9	0,666	Compliance	0,689	Compliance	0,497	Compliance
T10	0,581	Compliance	0,727	Compliance	0,327	Compliance

The observed consistency between the derivative-based functional trends and theoretical expectations validates the methodological rigor underlying the selection of criteria and the construction of the mathematical functions. Ultimately, the integration of functional and statistical perspectives demonstrates that the dependent–independent variable relationships are represented in a coherent, meaningful, and theoretically grounded manner thereby enhancing the analytical robustness, practical applicability, and scientific contribution of the proposed model.

4.4. Simulation Analysis

In mathematical modeling, the variance homogeneity of the results or quantitative values obtained within the created scenarios validates the robustness and stability of the model (Keshavarz-Ghorabaee et al., 2021). In this context, 10 scenarios were created in the research (10 decision matrices) were provided by assigning different values to traffic criteria, and the homogeneity of the scenarios was evaluated through ADM (Analysis of Means) based on Levene's test for variances.

In this study, the ten scenarios were designed on a simulation-based framework to evaluate the performance and stability of the proposed method. These scenarios were generated using hypothetical (representative) values rather than real-world data. Such an approach is widely adopted in the multi-criteria decision-making (MCDM) literature to assess the sensitivity, consistency, and variance homogeneity of decision models. In each scenario, the same decision criteria were retained, while the criterion values were varied across different distributions to construct ten distinct decision matrices. This allowed for the assessment of the model's stability under varying data conditions, and the homogeneity of the obtained results was statistically verified through Levene's test for equality of variances and the Analysis of Means (ADM) method (Keshavarz-Ghorabaee et al., 2021).

The primary objective of this approach was to demonstrate the robustness and generalizability of the proposed method independent of any specific dataset. Hence, the use of simulation-based scenario generation represents an accepted and well-established practice in the validation of MCDM methodologies.

In the ADM analysis, the visual figure primarily explains three components. The first is the overall mean ADM, represented as the central line; the second is the upper decision limit (UDL); and finally, the lower decision limit (LDL). When the standard deviation for a specific group (or cluster) exceeds the decision limits, this indicates a significant deviation from the general ADM average and shows variance heterogeneity. Conversely, if the standard deviations of all clusters remain within the UDL and LDL limits, it reveals variance homogeneity (Keshavarz-Ghorabaee et al., 2021). In this context, the visual output of the ADM analysis is shown in Figure 4.

As depicted in Figure 4, the ADM values calculated for each scenario remain within the bounds defined by the UDL and LDL. This indicates that the variances in the assigned weights across all scenarios exhibit consistency and homogeneity. Additionally, this finding was corroborated through the application of the Levene Test. The primary statistical outcomes of the Levene Test are summarized in Table 12.

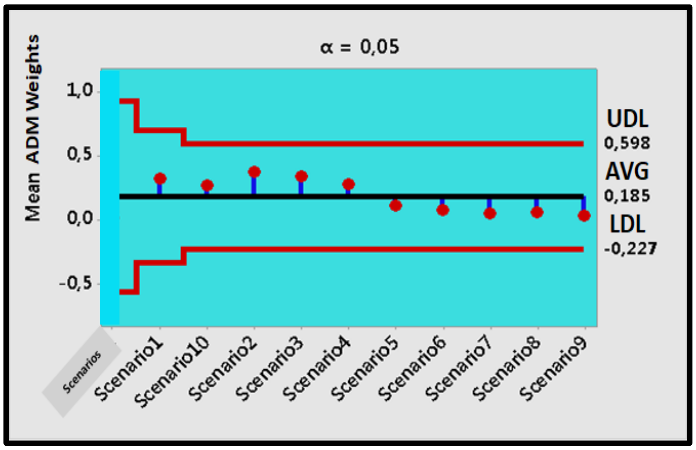

Figure 4. ADM Visual

Table 12. Levene statistical score

Levene Statistic	df1	df2	Sig.
0,142	2	10	0,156

Note: *p***<.05

As shown in Table 12, the *p*-value (p = 0.156) is greater than the significance threshold of 0.05, validating the consistency of variances in the criterion weights across the scenarios. In conclusion, the simulation analysis underscores the robustness and reliability of the CBCE method.

5. Discussion

In the field of traffic safety, the optimal spatial distribution of traffic enforcement units plays a decisive role in reducing accidents and enhancing monitoring efficiency (Siri et al., 2022). Strategic deployment enables continuous supervision and rapid response in high-risk areas through the efficient use of limited resources (Mandhare et al., 2021). Empirical findings demonstrate that concentrating enforcement in accident-prone zones effectively reduces both accident frequency and severity (Prothmann et al., 2011). Analytical and mathematical modeling approaches, particularly data-driven optimization frameworks, have proven valuable in formulating sustainable, evidence-based traffic management strategies (Theo et al., 2017; Gupta, 2017). Within this context, the present study introduces a comprehensive traffic model CBCE developed to determine the optimal regional distribution of traffic units for minimizing or preventing accidents.

In the proposed framework, traffic accidents are defined as the dependent variable, while ten traffic-related factors identified through expert evaluation serve as independent variables. A decision matrix was constructed using hypothetical six-year data from two regions. The CRITIC method was first applied to compute the objective weights of the independent variables, followed by Curve Estimation analysis using eleven distinct functional forms to model their effects on accident rates. Based on these results, the optimal number of enforcement units for each region was determined. Sensitivity, comparative, and simulation analyses confirmed the model's accuracy, reliability, and robustness, respectively.

Although the existing literature offers numerous studies on the determinants of traffic accidents, research specifically addressing the optimal distribution of enforcement units remains limited. Prior studies have utilized diverse analytical techniques panel data (Beenstock, 2001), structural equation modeling (Eygü, 2018), principal component analysis (Tercan & Beşdok, 2018), logit regression (Wahi et al., 2018), linear regression (Elvik et al., 2022), and MCDM methods (Kılıç and Asal, 2024). However, the CBCE model distinguishes itself by integrating multiple methodologies CRITIC for weighting, Curve Estimation for functional modeling, and a mathematical optimization framework for determining impact magnitudes thereby providing a more comprehensive and realistic representation of variable relationships.

Human-related factors were intentionally excluded due to their complexity, variability, and subjectivity (Hu et al., 2020; Modipa, 2022). These factors can fluctuate rapidly within short timeframes and vary among individuals, undermining analytical objectivity. In contrast, the selected traffic variables represent objective, universally observable criteria that all drivers encounter. The assumption is that increasing the number and visibility of traffic units indirectly improves human-related factors by enhancing driver awareness and compliance.

The study's scope is limited to a six-year dataset for each region; extending the temporal range could further refine model accuracy. Future studies may benefit from incorporating dynamic regional data, evolving infrastructural conditions, and technological advancements. Moreover, comparisons with alternative analytical techniques such as nonlinear canonical correlation or clustering methods could enhance understanding of the model's stability and generalizability.

The CBCE method offers an innovative, multidimensional, and flexible approach to optimization-based analyses of variables influencing traffic accidents. Its primary advantage lies in its ability to move beyond the constraints of a single functional form by evaluating eleven distinct regression functions defined in the SPSS literature and selecting the most statistically significant model based on the p-value. In cases where significance levels are equal, the coefficient of determination (R^2) is used as a secondary criterion to enhance model reliability. This dual-criterion framework strengthens the statistical robustness of the model, while the combined use of derivative and integral analyses enables the evaluation of both short- and long-term effects of variables in a dynamic and cumulative manner.

Consequently, CBCE not only captures instantaneous effects but also reveals the overall temporal dynamics of change. Furthermore, by considering regional variations and spatial dependencies, the method allows for more precise, location-specific analyses. The main limitation of CBCE is that, in cases involving a large number of dependent and independent variables, the mathematical computations become complex and time-consuming. However, this drawback is outweighed by the method's analytical depth and theoretical coherence.

Distinct from traditional models that rely solely on linear relationships, CBCE incorporates derivative and integral-based functional flexibility to effectively capture nonlinear interactions among variables. In doing so, it fills a long-standing methodological gap in the literature namely, the lack of modeling approaches grounded in functional flexibility and cumulative effect analysis between dependent and independent variables. Beyond traffic safety, CBCE provides a robust, reliable, and highly adaptable methodological framework applicable to various multidimensional systems, including healthcare, energy, and logistics, thereby making a distinctive and valuable contribution to the scientific literature.

Ethics Committee Approval Statement

This study does not involve human participants, animal subjects, or experimental procedures. The data used was not collected through observations or experiments; therefore, ethics committee's approval was not sought.

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