Identification of Road Crash Severity Ranking by Integrating the Multi-Criteria Decision-Making Approach

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Key Findings

- The integrated application of a multi-criteria decision-making approach for crash severity analysis and ranking has the potential to modify traditional methods.
- The existing step-wise framework of AHP and TOPSIS methods supports the integrated severity analysis of injury classified crashes.
- Effective implementation of research can provide a clear base to develop and monitor priority-based road safety improvement policies and strategies.

Abstract

This research aims to provide a novel approach for analysing road crash severity ranking by integrating all injury classified crash types. The road crash data of all Indian states (i.e., Andhrapradesh, Arunachal Pradesh, Bihar, etc.) for 2019 were incorporated to analyse severity rankings by using multi-criteria decision-making (MCDM) methods. Two of these methods – the Analytical Hierarchy Process (AHP) and Technique for Order Performance by Similarity to an Ideal Solution (TOPSIS) – were applied. The application of MCDM methods easily incorporated the injury classified crash data and provided clear rankings. Further, the correlation analysis of rankings provided by both MCDM methods proved the validity of the proposed research. Therefore, this approach is considered to have great potential to reform conventional severity ranking practices.

Keywords

road crashes, severity analysis, ranking, multi-criteria decision making

Glossary

Road crash victim: A person/persons involved in a road crash
Fatal injury crash: A crash that costs human life or lives
Grievous injury crash: A crash that causes serious injuries to victims with an immediate need of hospitalisation
Minor injury crash: A crash that causes minor injury with no need for hospitalisation
Non-injury crash: A crash with no physical harm to road users
Criteria (C): The analysis standards for decision making
Alternative (A): The possible choices to be analysed for decision making
Indian States: The administrative parts of the country having their own 'state government', under the Government of India.

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Introduction

Road crashes cause 1.35 million deaths each year. It is one of the leading causes of fatalities for children-young adults (World Health Organization 2017). Low-income countries have three times the fatality rate in road crashes than higher-income countries (World Health Organization 2018). The higher injury and fatality rates are heavily affecting the financial and cultural advances of developing countries (Ruikar 2013). As one of the developing economies, India is also being affected by increasing road crash fatalities with rapid growth in motorised traffic (Gururaj 2013). Fifteen road crash deaths and more than fifty injuries are being reported every hour in India, due to the lack of integrated road safety efforts and safety improvement programs (Singh 2017). The lack of proper crash data collection and reporting systems makes mathematical modelling and analysis of Indian road crashes more challenging (Chatterjee, Bandyopadhyaya, & Mitra 2020). The total number of road crashes in India has declined in the last five years but the fatality numbers have increased. The current alarming situation suggests an urgent need for a nationwide crash severity analysis.

Crash severity analysis is a complex process as the crash is triggered by several factors. Many researchers have made significant efforts to evaluate crash severity with contributory factors such as human, road environmental, and vehicle factors (Al-Ghamdi, 2002; De Leur & Sayed 2002; Yamamoto & Shankar, 2004; Savolainen & Mannering 2007; Sze & Wong 2007; Pei & Fu 2014; George, Athanasios, & George 2017). However, the majority of approaches have been formulated with a focus on fatalities and severe injuries only (Shibata & Fukuda 1994; Abdel-Aty, Chen, & Schott 1998; Kockelman & Kweon 2002; Lee & Mannering 2002). Risk indicators for severity analysis have been solely formulated by considering the ratio of absolute fatality values and exposure indicators such as registered vehicles, population, etc. Based on the reports published by the Indian Ministry of Road Transport and Highways, the severity of road crashes is analysed by just considering the fatality ratio per 100 crashes. The state-wise severity ranking also uses this ratio (Ministry of Road Transport & Highways 2016; Ministry of Road Transport & Highways 2018; Ministry of Road Transport & Highways 2019). These practices suggest that there is a clear lack of integration for the available data on grievous injury, minor injury, and no injury crashes to analyse severity and rank the selected states accordingly. However, it is advisable to incorporate a wider variety of criteria for a robust severity analysis (Bao et al. 2012; Bham, Manepalli, & Samaranayke 2019).

Single criteria-based analysis may not provide robust results but the integration of more criteria can create a complex analysis structure. The successful introduction of multi-criteria decision-making (MCDM) methods makes the complex analysis much easier and more flexible (Hwang Ching-Lai, 1981; Kumar & Ray, 2014; Mitra et al. 2015). The various MCDM methods including the Analytic Hierarchy Process (AHP), Weighted Product Model (WPM), Fuzzy Analytic Hierarchy Process, Revised Analytic Hierarchy Process (RAHP), Weighted Sum Model (WSM), Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS), Elimination and Choice Translating Reality (ELECTRE), and many more have been developed by researchers with different approaches and computational logic (Sabaei, Erkoyuncu, & Roy 2015; Jayant & Sharma 2018). Some researchers applied several weighting methods such as factor analysis (FA), equal weighting method, budget allocation, Data Envelopment Analysis (DEA), and summarised the statistical nature of these methods (Hermans, Bossche, & Wets 2008). Further, some literature applied MCDM methods to solve selection-based problems in transportation planning and engineering (Abdullah & Zamri 2010; Coll, Moutari, & Marshall 2013; Fancello, Carta, & Fadda 2015; Hsu, Lian, & Huang 2020; Moslem & Çelikbilek 2020; Duleba 2020; Ebrahimi & Bridgelall 2021; Ortega et al. 2021; Yakar 2021). However, the absence of research articles applying MCDM methods to estimate road crash severity is evident.

This article aims to evaluate the severity of road crashes by considering all types of crashes (i.e., fatal injury crash, grievous injury crash, minor injury crash, and non-injury crash) and to develop a novel severity ranking approach. Therefore, the MCDM methods are applied to the crash data of 35 Indian states (i.e., Andhrapradesh, Arunachal Pradesh, Bihar, etc.) to achieve this goal.

Methodology

To analyse road crash severity, the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solutions (TOPSIS) were selected. As per the Ministry of Road Transport & Highways (MoRTH) guidelines, every Indian State must periodically submit data on traumatic and non-traumatic crashes. As per Table 1, data on road crashes for 2019 were collected from the annual Indian road crash report (Ministry of Road Transport & Highways 2019). A description of the detailed steps of both the selected MCDM methods is followed by considering the injury classified crash types as the criteria and the Indian States as the decision alternatives as per the following sections.

The Analytic Hierarchy Process (AHP)

Saaty developed a novel method, titled as Analytic Hierarchy Process (AHP) to simplify complex decision making (Saaty 1977). Later, the AHP was applied to solve competitive market sector problems (Saaty 1983), further developed (Saaty 1986), and used to solve a variety of decision-making problems (Jensen 1984; Saaty 1990). Many scientists (e.g. Harker & Vargas 1987; Dyer 1990) critically observed the mathematical structure of AHP

Table 1. Indian state-wise road crash data

	Fatal injury crash (C1)	Grievous injury crash (C2)	Minor injury crash (C3)	Non-injury crash (C4)
Andhra Pradesh (A1)	7389	4053	9235	1315
Arunachal Pradesh (A2)	108	79	43	7
Assam (A3)	3019	4217	664	450
Bihar (A4)	6731	2546	239	491
Chhattisgarh (A5)	4603	1809	5799	1688
Goa (A6)	283	196	769	2192
Gujarat (A7)	6726	5826	3418	1076
Haryana (A8)	4684	1575	4223	462
Himachal Pradesh (A9)	930	932	840	171
Jammu & Kashmir (A10)	762	2470	1751	813
Jharkhand (A11)	3414	1481	215	107
Karnataka (A12)	10060	17487	9768	3343
Kerala (A13)	4183	29569	6043	1316
Madhya Pradesh (A14)	10182	5427	30593	4467
Maharashtra (A15)	11787	12197	5473	3468
Manipur (A16)	146	152	356	18
Meghalaya (A17)	169	117	105	91
Mizoram (A18)	46	6	5	5
Nagaland (A19)	24	69	92	173
Orissa (A20)	4844	4152	1863	205
Punjab (A21)	4190	1519	555	84
Rajasthan (A22)	9471	4226	8966	817
Sikkim (A23)	61	50	42	9
Tamil Nadu (A24)	9813	3771	42885	759
Telangana (A25)	6472	2190	10792	2116
Tripura (A26)	224	409	8	14
Uttarakhand (A27)	750	472	101	29
Uttar Pradesh (A28)	19731	13651	7739	1451
West Bengal (A29)	5120	4734	304	1
A & N Islands (A30)	20	63	92	55
Chandigarh (A31)	100	14	162	29
D & N Haveli (A32)	48	18	1	2
Daman & Diu (A33)	23	28	11	7
Delhi (A34)	1433	666	3459	52
Puducherry (A35)	143	587	605	57

(Harker & Vargas 1990). With its simple structure and ease of application, the method has become widely accepted. This is a simple weighting method, providing a framework for decision-makers. The method is divided into the following steps:

Step 1. Development of the decision hierarchy

The problem-based hierarchy for decision-making is developed by placing the objectives at the topmost level and the selected alternatives at the following levels of the hierarchy. Accordingly, the intermediate hierarchy levels are filled with selected criteria and secondary criteria. Therefore, the complexity of the decision hierarchy governs the number of levels for effective decision-making.

Step 2. Synthesis of comparison pairwise matrix

The decision-maker has to generate a comparison pairwise matrix for every hierarchical level. For 'M' numbers of alternatives and 'N' numbers of criteria, a 'j' number of alternative judgments matrix has to be formulated of M × M order. The criteria comparison matrix of N × N order is also formulated. The decision-maker has to define the linguistic importance for every criteria over the rest of the criteria for defining the weights. Then, the numeric scores (C_{ij}) are assigned to every linguistically defined comparative importance as per Table 2. Further, an N × N matrix of the criteria comparison (C_1) is formulated with C_{ij} scores.

$$C_1 = \begin{bmatrix} 1 & C_{12} & \dots & C_{1N} \\ C_{21} & 1 & \dots & C_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ C_{N1} & C_{N2} & \dots & 1 \end{bmatrix}$$

Here $C_{ij} = 1$ when $i = j$

Step 3. Analysis of comparative criteria weights

The geometric mean (GM) for all the matrix rows is calculated by applying equation 1. Then, the comparative criteria weight (W_i) for any i^{th} criteria is calculated by applying equation 2.

$$GM_i = \left\{ \prod_{j=1}^{N} C_{ij} \right\}^{1/N} \tag{1}$$

$$W_i = \frac{GM_i}{\sum_{I=1}^{N} GM_i} \tag{2}$$

Now the matrix C_3 and C_4 are formulated in such a way that both must satisfy the following relations.

$$C_3 = C_1 \times C_2 \, ; C_4 = {}^{C_3}/_{C_2} \tag{3}$$

Here $C_2 = [W_1 \ W_2 \ W_3 \dots W_N]^T$

The average of the C_4 matrix is used for calculating the Eigenvector (λ_{max}). Finally, the consistency check is done with the help of the consistency ratio (CR) and the consistency index (CI). The standard values for the random index are considered as per Table 3. If the calculated value for CR is 0.1 or less; the decision is recognised and the calculated W_i values are termed as consistent. Else, the decision-maker has to reassess the comparative matrix with revised C_{ij} scores.

$$CR = {}^{CI}/_{RI} \tag{4}$$

$$CI = {}^{\lambda_{max} - N}/_{N - 1} \tag{5}$$

Table 2. Saaty's scale for comparative importance

Score	Definition of importance	Description
1	Equally important	For equally contributed comparative criteria
3	Moderately important	Particular criteria are to some extent complementary than the other criteria
5	Essentially or strongly important	Particular criteria are strongly complementary than the other criteria
7	Very strongly important	Particular criteria are very strongly dominating over the other criteria
9	Extremely important	Clear dominance of particular criteria over the other criteria
2,4,6,8	Between two adjacent values	Intermediate nature of criteria
$^1/_3$, $^1/_4$, $^1/_5$ ….	Inverse comparative values	Inversely significant criteria over the other criteria

Source: Saaty (1990)

Table 3. Standard random index values

C_n	1	2	3	4	5	6	7	8	9
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Source: Saaty (1990)

Here; C_n= number of criteria, RI = random index

Step 4. Formulating the priority score

The priority for every alternative is identified using the normalised alternative values (a_{ij}). The associated criterion weights are also integrated within the formulation by using the following equations:

$$\text{Priority score } A_{AHP} = \max\left(\sum_{j=1}^{N} a_{ij} W_j\right) \quad (6)$$

where i = 1, 2,……, M; j = 1, 2,….., N

Technique for Order Performance by Similarity to Ideal Solution (TOPSIS)

Yoon and Hwang in 1981 (Hwang Ching-Lai 1981) invented the TOPSIS method. Rather than following a complex approach, the TOPSIS follows a modest system of weighting. The method delivers conclusions based on the distance measuring approach. The final closeness value of any particular alternative results in values adjacent to the ideal suitable solution and away from the solution negative.

Step 1. The decision matrix is normalised by equation 7:

$$N_{ij} = \frac{X_{ij}}{\sqrt{\sum_{i=1}^{M} X^2}} \quad (7)$$

where i = 1, 2,……, M; j = 1, 2,….., N

Here N_{ij} are the normalised values

Step 2. Formulation of normalised weighted values

The next step is to multiply the criteria weights (W_{ij}) with the normalised matrix values (N_{ij}) by applying equation 8:

$$V_{ij} = W_{ij} \times N_{ij} \quad (8)$$

where i = 1, 2, ……, M; j = 1, 2, ….., N

Step 3. Finding the ideal solution positive and solution negative

This step is very important for obtaining accurate results; as the TOPSIS approach considers the relative closeness values near to the ideal solution. The subsequent formulae are used for defining the ideal solution positive and solution negative.

Ideal solution positive:

$$[V_1^+, V_2^+, \ldots, V_N^+] = [(Max\, V_{ij} \mid i \in K), (Min\, V_{ij} \mid i \in K')] \quad (9)$$

Solution negative:

$$[V_1^-, V_2^-, \ldots, V_N^-] = [(Min\, V_{ij} \mid j \in K), (Max\, V_{ij} \mid j \in K')] \quad (10)$$

where K = criteria positive index set, K' = criteria negative index set

Step 4. Finding the distances from the ideal solution positive and solution negative

The distances from the ideal solution positive (S_i^+) and the solution negative (S_i^-) are identified by applying the following equations:

$$Si+ = \sqrt[2]{\left\{\sum_{j=1}^{N} (V_{ij} - V_j^+)^2\right\}} \quad (11)$$

$$Si- = \sqrt[2]{\left\{\sum_{j=1}^{N} (V_{ij} - V_j^-)^2\right\}} \quad (12)$$

where i = 1, 2,……, M; j = 1, 2,…..,N

Step 5. The final ranking is generated by considering the relative closeness values

$$C_i = {S_i^+} / {(S_i^+ - S_i^-)} \quad (13)$$

where i = 1, 2, ……, M

The final step of TOPSIS is to generate the ranking by analysing the relative closeness values of each alternative (C_i).

Analysis

The analysis began with the development of the decision hierarchy as per Figure 1. The principal objective (i.e., crash severity ranking) was placed at the 1st Level. Then, the 2nd level of the hierarchy was developed by adding the objective-oriented criteria. Finally (3rd Level), all 35 alternatives were placed to decide the rank according to the principal research objective. Then, the comparative importance scores were allocated to every criterion for effective pair-wise comparison (Table 4). Government officials, road safety auditors, and safety experts were consulted via group meetings to generate these scores. Saaty's comparative scale (Table 2) was taken as the reference to conclude the comparative scores based on the discussions. Table 4 highlights that fatal injury crashes (C1) have strong importance over grievous injury crashes (C2). The supremacy of grievous injury crash (C2) over minor injury crash (C3) was found to be strong and the importance of minor injury crashes (C3) over non-injury crashes (C4) was assessed as moderate. By following the described AHP steps, the local criteria weights were analysed as per Table 4.

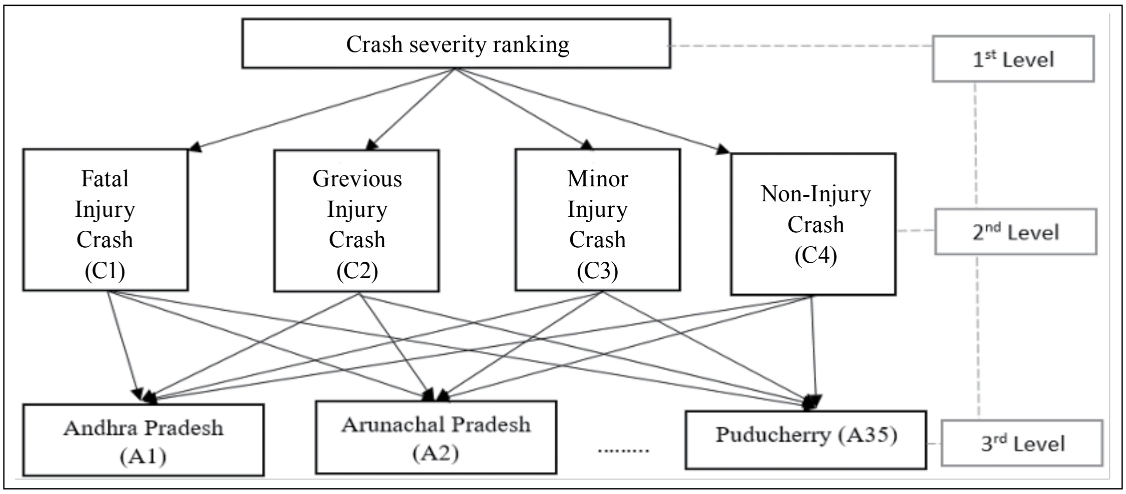

Figure 1. Hierarchy of decision making

Table 4. Pair-wise criteria comparison matrix

Criteria	C1	C2	C3	C4	Geometric mean (GM)	Normalised GM / criteria weights	Weighted sum value
C1	1	3	5	9	3.41	0.55	2.34
C2	1/3	1	6	8	2.00	0.32	1.38
C3	1/5	1/6	1	3	0.56	0.09	0.38
C4	1/9	1/8	1/3	1	0.26	0.04	0.17

Further, the consistency ratio (CR) of local criteria weights were analysed with consistency index (CI) and random index (RI) values as per the following calculations:

Here: Consistency index **(CI)** = $\frac{\lambda_{\max} - n}{n-1}$

where $$\lambda_{\max} = \frac{\left(\left(\frac{2.34}{0.55}\right)+\left(\frac{1.38}{0.32}\right)+\left(\frac{0.38}{0.09}\right)+\left(\frac{0.17}{0.04}\right)\right)}{4} = 4.22$$

Therefore **CI =** (4.22 – 4) / 3 = 0.07

$$\text{Consistency ratio } \mathbf{(CR)} = \frac{\text{Consitency index (CI)}}{\text{Random index (RI)}}$$

CR = 0.07/0.90 = 0.083

Here RI = 0.90 (As per Table 3)

The calculated CR value lay under the critical value (0.1). Therefore, the calculated local criteria weights were accepted as the global criteria weights for further analysis. For the present research, increases in fatalities, grievous injury, or minor injury escalate the severity value. Based on this fact, the first three criteria (i.e., C_1, C_2, C_3) were classified as the benefit criteria. Further, the values of Table 1 were normalised by applying equations 14 and 15.

$$\text{For benefit criteria (i. e., } C_1, C_2, C_3\text{),} \quad NV_{ij} = \frac{a_{ij}}{Max\ a_{ij}} \tag{14}$$

$$\text{For cost criteria, (i. e., } C_4\text{),} \quad NV_{ij} = \frac{Min\ a_{ij}}{a_{ij}} \tag{15}$$

Here NV_{ij} indicates the normalised value

Finally, Equation 16 was derived by integrating the global criteria weights with normalised values.

$$\begin{aligned} \text{Severity value} = ((&0.55 \times \text{NV of fatal injury crash}) \\ (&0.32 \times \text{NV of grievous injury crash}) + \\ (&0.09 \times \text{NV of minor injury crash}) + \\ (&0.04 \times \text{NV of non-injury crash})) \end{aligned} \tag{16}$$

Further, the AHP generated global criteria weights were integrated with the TOPSIS analysis. The rest of the TOPSIS analysis was done following the steps in the previous section. Table 6 presents the values for the distance from the ideal solution positive (S_i^+) and solution negative (S_i^-) with all the relative closeness values (C_i).

Table 5. The normalised values of alternatives and global criteria weights

	C1	C2	C3	C4
Weights →	**0.55**	**0.32**	**0.09**	**0.04**
A1	0.3745	0.1371	0.2153	0.0008
A2	0.0055	0.0027	0.0010	0.1429
A3	0.1530	0.1426	0.0155	0.0022
A4	0.3411	0.0861	0.0056	0.0020
A5	0.2333	0.0612	0.1352	0.0006
A6	0.0143	0.0066	0.0179	0.0005
A7	0.3409	0.1970	0.0797	0.0009
A8	0.2374	0.0533	0.0985	0.0022
A9	0.0471	0.0315	0.0196	0.0058
A10	0.0386	0.0835	0.0408	0.0012
A11	0.1730	0.0501	0.0050	0.0093
A12	0.5099	0.5914	0.2278	0.0003
A13	0.2120	1.0000	0.1409	0.0008
A14	0.5160	0.1835	0.7134	0.0002
A15	0.5974	0.4125	0.1276	0.0003
A16	0.0074	0.0051	0.0083	0.0556
A17	0.0086	0.0040	0.0024	0.0110
A18	0.0023	0.0002	0.0001	0.2000
A19	0.0012	0.0023	0.0021	0.0058
A20	0.2455	0.1404	0.0434	0.0049
A21	0.2124	0.0514	0.0129	0.0119
A22	0.4800	0.1429	0.2091	0.0012
A23	0.0031	0.0017	0.0010	0.1111
A24	0.4973	0.1275	1.0000	0.0013
A25	0.3280	0.0741	0.2516	0.0005
A26	0.0114	0.0138	0.0002	0.0714
A27	0.0380	0.0160	0.0024	0.0345
A28	1.0000	0.4617	0.1805	0.0007
A29	0.2595	0.1601	0.0071	1.0000
A30	0.0010	0.0021	0.0021	0.0182
A31	0.0051	0.0005	0.0038	0.0345
A32	0.0024	0.0006	0.0000	0.5000
A33	0.0012	0.0009	0.0003	0.1429
A34	0.0726	0.0225	0.0807	0.0192
A35	0.0072	0.0199	0.0141	0.0175

Table 6. Si+, Si- and Ci values of TOPSIS analysis

	S_i^+	S_i^-	C_i
A1	0.072807	0.000332	0.004538
A2	0.169889	0.000000	0.000001
A3	0.117324	0.000015	0.000131
A4	0.082698	0.000222	0.002681
A5	0.104028	0.000050	0.000478
A6	0.165974	0.000000	0.000000
A7	0.075624	0.000250	0.003292
A8	0.104230	0.000055	0.000530
A9	0.154343	0.000001	0.000004
A10	0.151977	0.000001	0.000004
A11	0.119619	0.000018	0.000149
A12	0.036216	0.001872	0.049144
A13	0.064577	0.001422	0.021542
A14	0.049030	0.001263	0.025109
A15	0.033893	0.002431	0.066917
A16	0.168981	0.000000	0.000001
A17	0.168752	0.000000	0.000001
A18	0.171128	0.000000	0.000001
A19	0.171209	0.000000	0.000001
A20	0.096995	0.000072	0.000741
A21	0.110454	0.000037	0.000336
A22	0.057525	0.000865	0.014813
A23	0.170736	0.000000	0.000001
A24	0.053738	0.001205	0.021931
A25	0.084058	0.000189	0.002240
A26	0.167002	0.000000	0.000002
A27	0.158625	0.000000	0.000003
A28	0.010750	0.016863	0.610688
A29	0.093218	0.000092	0.000982
A30	0.171331	0.000000	0.000001
A31	0.170193	0.000000	0.000001
A32	0.171059	0.000000	0.000001
A33	0.171427	0.000000	0.000001
A34	0.147338	0.000001	0.000009
A35	0.167597	0.000000	0.000001

Results and Discussion

The AHP based severity values and the TOPSIS based relative closeness values were placed in descending order to generate the final severity ranking (Table 7). The combined plot (Figure 2) highlights the similarity between the AHP severity values and TOPSIS C_p values. Alternative 28 (A28) Uttar Pradesh was ranked no. 1 based on the AHP and TOPSIS methods. Maharashtra (A15), Karnataka (A12), Madhya Pradesh (A14), Tamil Nadu (A24), Kerala (A13), Rajasthan (A22), Andhra Pradesh (A1), and Gujarat (A7) were placed within the top ten ranks by both methods. However, West Bengal (A29) ranked 10th by AHP and 12th by the TOPSIS method. This dissimilarity in the ranking was also observed for other alternatives. Therefore, correlation analysis was conducted according to Equation 17.

$$\text{Rank Correlation coefficient } (\mathbf{Rs}) = 1 - \frac{6\sum D^2}{M(M^2-1)} \quad (17)$$

Here 'M' is the total number of Alternatives (i.e., 35). 'D' represents the difference between the rankings provided to each Alternative.

The rank correlation coefficient (R_s) resulted as 0.978. The highest value of R_s (i.e., 0.978) suggests that the rankings generated by the two MCDM methods are in the highest agreement. Further, a two-tailed t-test was conducted to determine the statistical significance of the AHP severity values and TOPSIS relative closeness values. The equal variance null hypothesis (H_0) is assumed for AHP severity values and TOPSIS relative closeness values. With 95% accuracy, the p-value was greater than 0.05 (p-value > 0.05). The greater p-value suggests that the null hypothesis (H_0) be accepted (Table 8). Therefore, the statistical success of the proposed approach is proved with the rank correlation coefficient (R_s) and t-test analysis.

A Pareto distribution curve is plotted in Figure 3 with AHP severity values and percentage cumulative severity values of each alternative. The distribution suggests that the first fourteen ranked Indian States are causing 85% of cumulative injury severity. This distribution should act as the decision-making base for policymakers, decision-makers, and government officials to formulate priority-based reform strategies.

The detailed analysis states that the proposed approach is data-centric. As a drawback, the extracted rankings

Table 7. Final ranking provided by both MCDM methods

AHP			TOPSIS		
Rank	**States**	**Severity value**	**Rank**	**States**	**Relative closeness value**
1	Uttar Pradesh (A28)	0.7140	1	Uttar Pradesh (A28)	0.7694
2	Karnataka (A12)	0.4902	2	Maharashtra (A15)	0.5465
3	Maharashtra (A15)	0.4721	3	Karnataka (A12)	0.5186
4	Kerala (A13)	0.4493	4	Madhya Pradesh (A14)	0.4551
5	Madhya Pradesh (A14)	0.4068	5	Tamil Nadu (A24)	0.4416
6	Tamil Nadu (A24)	0.4044	6	Rajasthan (A22)	0.4137
7	Rajasthan (A22)	0.3286	7	Kerala (A13)	0.4086
8	Andhra Pradesh (A1)	0.2692	8	Andhra Pradesh (A1)	0.3311
9	Gujarat (A7)	0.2577	9	Gujarat (A7)	0.3114
10	West Bengal (A29)	0.2346	10	Bihar (A4)	0.2966
11	Telangana (A25)	0.2268	11	Telangana (A25)	0.2863
12	Bihar (A4)	0.2158	12	West Bengal (A29)	0.2420
13	Orissa (A20)	0.1841	13	Orissa (A20)	0.2279
14	Chhattisgarh (A5)	0.1601	14	Haryana (A8)	0.2113
15	Haryana (A8)	0.1566	15	Chhattisgarh (A5)	0.2068
16	Punjab (A21)	0.1349	16	Punjab (A21)	0.1911

AHP			TOPSIS		
17	Assam (A3)	0.1313	17	Jharkhand (A11)	0.1595
18	Jharkhand (A11)	0.1120	18	Assam (A3)	0.1553
19	Delhi (A34)	0.0552	19	Delhi (A34)	0.0834
20	Jammu & Kashmir (A10)	0.0517	20	Himachal Pradesh (A9)	0.0672
21	Himachal Pradesh (A9)	0.0380	21	Jammu & Kashmir (A10)	0.0666
22	Uttarakhand (A27)	0.0276	22	Uttarakhand (A27)	0.0627
23	D & N Haveli (A32)	0.0215	23	Tripura (A26)	0.0543
24	Tripura (A26)	0.0135	24	Puducherry (A35)	0.0537
25	Puducherry (A35)	0.0123	25	Manipur (A16)	0.0534
26	Goa (A6)	0.0116	26	Arunachal Pradesh (A2)	0.0532
27	Arunachal Pradesh (A2)	0.0097	27	D & N Haveli (A32)	0.0530
28	Mizoram (A18)	0.0094	28	Sikkim (A23)	0.0530
29	Manipur (A16)	0.0087	29	Mizoram (A18)	0.0530
30	Sikkim (A23)	0.0068	30	Chandigarh (A31)	0.0529
31	Daman & Diu (A33)	0.0067	31	Daman & Diu (A33)	0.0529
32	Meghalaya (A17)	0.0066	32	Meghalaya (A17)	0.0526
33	Chandigarh (A31)	0.0047	33	A & N Islands (A30)	0.0524
34	A & N Islands (A30)	0.0022	34	Nagaland (A19)	0.0510
35	Nagaland (A19)	0.0018	35	Goa (A6)	0.0305

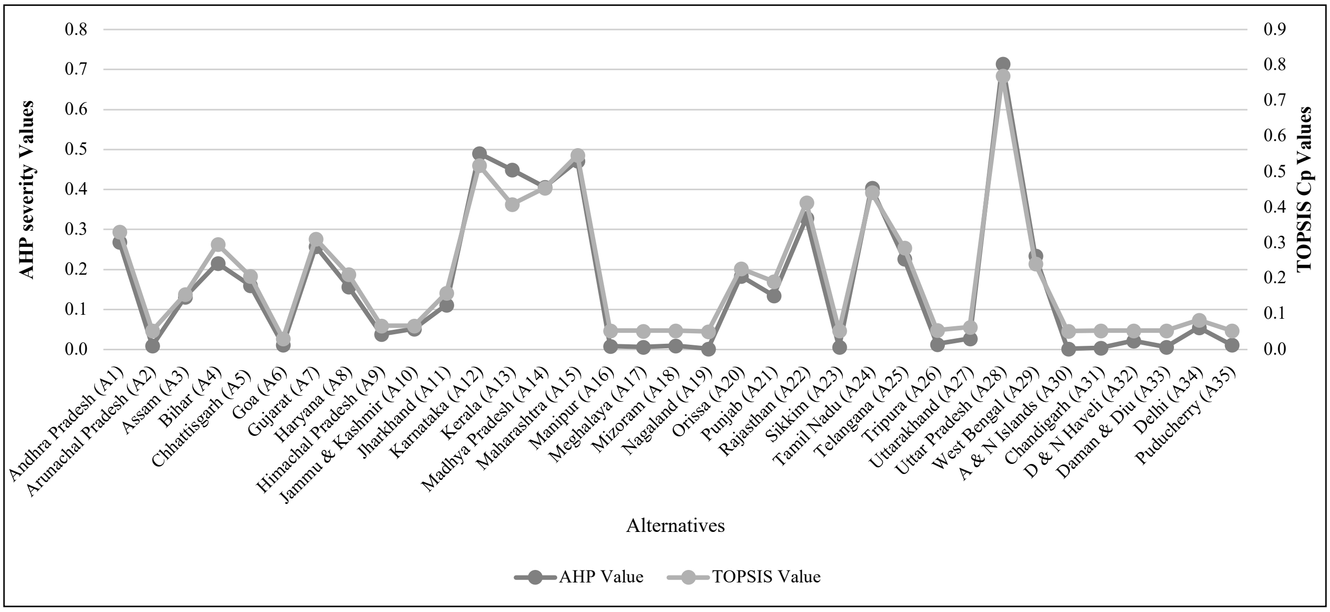

Figure 2. AHP severity values and TOPSIS Cp values

Table 8. t-Test: Two-Sample assuming equal variance

	AHP Severity Value	TOPSIS Relative Closeness value
Mean (μ)	0.1610	0.2034
Variance (σ^2)	0.0334	0.0343
Observations (n)	35.00	35.00
Hypothesised mean difference	0.0000	
t Stat	-0.9624	
P(T<=t) two-tail	0.3393	
t Critical two-tail	1.9955	

may vary depending on the availability and accuracy of the crash data. The current Indian road crash scenario highlights that the number of fatal road crashes is much higher than other types of crashes. Based on this the global criteria weight for fatal injury crashes (C_1) has been concluded to be the highest with high importance in severity analysis, and accordingly, the Indian States with the highest number of fatalities have been placed in the top rankings. However, the severity significance of other types of crashes cannot be overstated due to their smaller numbers. Province-wise road safety and crash severity have been analysed in some research (Rosić et al. 2017; Castro-Nuño & Arévalo-Quijada 2018) by integrating multiple factors but the absence of integration of minor injury and non-injury crash is evident. Therefore, the proposed approach integrates all types of crash severity levels for robust severity analysis. The Government of India is also taking steps to enhance countrywide road safety and has initiated an integrated Road Accident Database (iRAD) program. As a result, it has become easier to collect road crash data from all the stakeholders. Therefore, the iRAD integration of this proposed method will provide robust road crash severity rankings of Indian states.

Conclusions

The relevance of minor injury crashes and non-injury crashes is often ignored when undertaking severity analysis. The lack of a State-by-State severity analysis and ranking approach is clear. Therefore, this paper aimed to examine the conventional road crash severity analysis practices and advanced a novel integrated analysis approach through MCDM integration of fatal injury, grievous injury, minor injury, and non-injury crashes. The MCDM methods were used to generate rankings for 35 Indian States based on their crash severity condition. Results have been submitted to road safety stakeholders and found to be very relevant. Following are the important highlights of this paper:

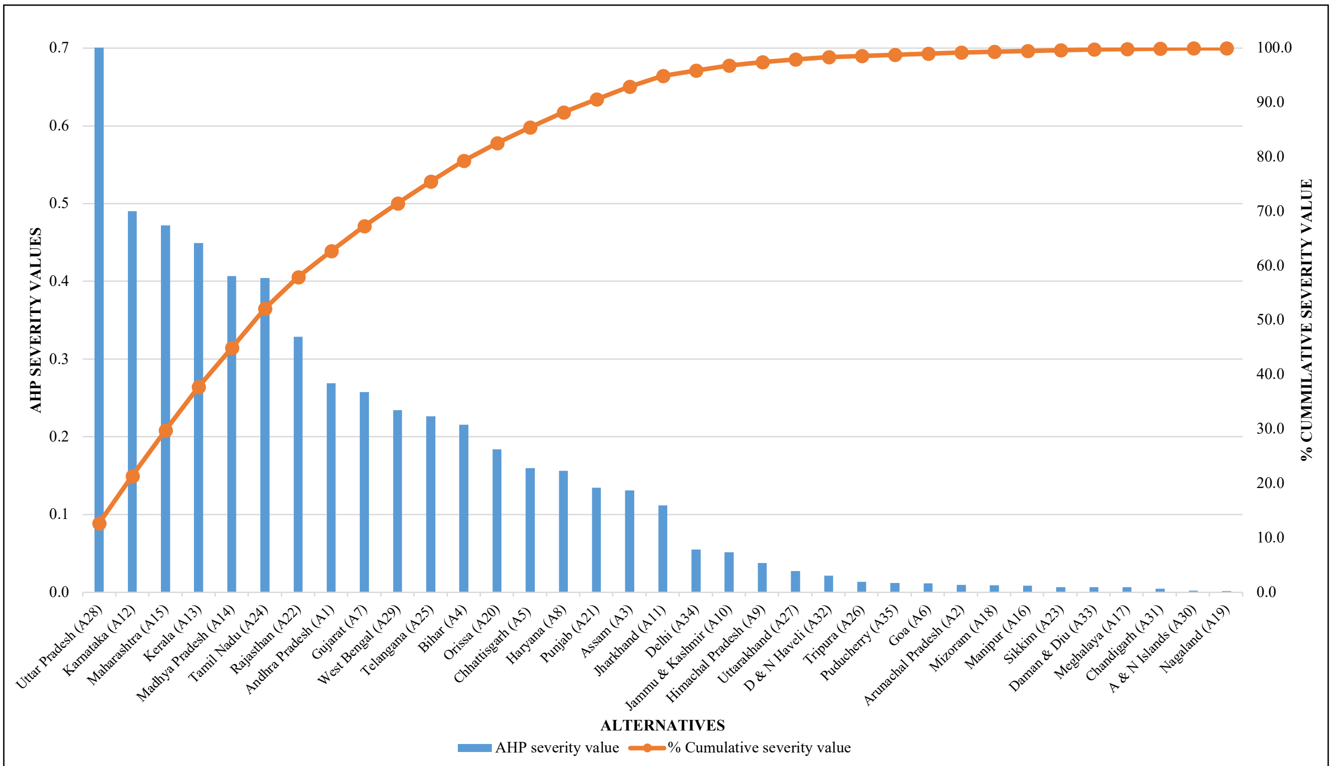

Figure 3. Cumulative injury severity distribution

- The present research highlights how the proposed approach could undertake the highest integration of all injury classified crash types compared with conventional severity analysis practices.
- The Rankings generated by AHP and TOPSIS methods are in the highest agreement.
- Providing strong evidence of actual conditions, this integrated crash severity ranking approach could prove to be a handy tool to form priority-based interventions strategies.
- The extracted rankings are found very relevant to actual Indian road crash conditions.
- The transfer and application of the proposed approach are possible by modifying the principal data table according to the road crash data of each State.

The proposed approach provided relevant results with limited classified data (i.e., injury classified crash data). The government officials, policymakers, and road safety experts must provide special attention to the top-ranked Indian states with combined efforts. Further, the research priorities with special road safety fund allocation should be provided to top-ranked Indian states. Thus, it would be worthwhile to apply this approach in different settings (e.g., police stations, different zones of the city, etc.). Future research in this direction is possible with fuzzy MCDM methods and different research criteria (e.g., registered vehicles, traffic volumes, etc.).

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Conflicts of Interest

The authors declare that there is no conflict of interest.

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