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Hybrid Analytic Hierarchy Process & Goal Programming Approach for Multi-Criteria Decision Making in Road Traffic Accident Management: Optimum Resource Planning

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ABSTRACT: Road traffic accidents are a complex, multi-dimensional problem influenced by behavioral, mechanical, infrastructural, environmental, and enforcement factors. This paper presents a novel hybrid MCDA framework that integrates the AHP to prioritize multiple contributing criteria and GP to optimize conflicting road safety objectives under resource constraints. Expert judgments are systematically quantified through AHP to assign weights to nine key criteria affecting accident severity. These weights inform the GP model's objective function, which minimizes weighted deviations from multiple safety goals, including reducing fatalities, injuries, accident frequency, and improving emergency response and public awareness. The GP model optimally allocates limited resources across targeted interventions. Numerical results demonstrate the model's flexibility and effectiveness in balancing competing objectives, supporting informed and transparent policymaking. The methodology is adaptable to diverse geographic contexts and offers a structured approach for Multi-Criteria transportation safety management.

Key Words: Road Accident Severity, Analytic Hierarchy Process (AHP), Goal Programming (GP), Multi-Criteria Decision Making (MCDM), traffic safety.

Contents

1. Introduction

One of the important and main causes of mortality and serious injury in the globe is traffic accidents. Around 1.19 million people lost their lives in traffic accidents every year, and 50 million more get non-fatal injuries, many of which lead to permanent impairments, according to "World Health Organization's Global Status Report on Road Safety 2023" [1]. The most common reason for mortality happens between the ages of 5 and 29; is currently traffic-related injuries. The economic burden is also staggering: road crashes cost countries an estimated 2% to 3% of their gross domestic product (GDP), with higher proportions in low- and middle-income economies [2].

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The multifactorial nature of traffic accidents complicates mitigation strategies. In fast-growing urban regions, rising motorization rates often outpace infrastructure development, leading to increased congestion, poor signage, and compromised traffic flow. In contrast, rural and peri-urban areas frequently suffer from inadequate emergency medical services, weak traffic law enforcement, and low public awareness, all contributing to higher post-crash fatality rates. For instance, data from the OECD's International Transport Forum shows that in certain low-income regions, average ambulance response times exceed 25 minutes, and nearly 60% of accident victims do not receive care within the first hour [4].

Moreover, behavioral risk factors such as distracted driving, alcohol use, and speeding remain prevalent. The WHO estimates that 1 in 4 road deaths involves alcohol impairment, and helmet use among motorcyclists remains below 50% in many countries [1]. Simultaneously, infrastructural and vehicle-related issues like poorly maintained roads, lack of pedestrian crossings, and inadequate vehicle inspections continue to contribute to the overall accident burden.

Traditional decision-making frameworks, often based solely on historical crash statistics or single-objective optimization models, fail to account for the complex interplay of these factors. More importantly, they lack the capacity to incorporate expert judgment and multi-goal prioritization under resource constraints. Consider a case where a country increases infrastructure investment by 30%, yet sees only marginal improvements in fatality rates due to poor driver compliance and emergency response delays. This shows the need for a more integrative, multi-dimensional planning approach.

To address this gap, this study introduces a hybrid decision-support framework that combines the AHP and GP. The AHP enables structured expert judgment to prioritize contributing factors to accident severity, while the GP model allocates limited resources across competing safety goals such as reducing fatalities, minimizing injuries, improving emergency responses, and enhancing public awareness by minimizing weighted deviations from desired targets. The table 1 shows the Comparative Road Accident Statistics (2023) – Linked to Safety Goals as shown in Figure 1

The objective of this paper is to formulate and demonstrate an adaptable, data-informed, and goal-driven optimization model suitable for road safety planning in a variety of regional contexts.

Table 1: Comparative Road Accident Statistics (2023)

Indicator	**Global (WHO, 2023)**	**India (MoRTH, 2023)**	**Karnataka (GoK, 2023)**	**Bengaluru (BTP, 2023)**
Road traffic deaths (G1)	~1.19 million	172,890	12,321	921
Serious injuries (G2)	~50 million	450,000+	52,547	7,500+
Accident frequency (G3)	>55 million	461,312	43,440	4,100
Emergency response efficiency (G4)	Avg. EMS arrival 15–20 min	15–20 min (urban), >25 min (rural)	18–25 min	12–15 min
Public awareness & training (G5)	<40% countries run campaigns	Road Safety Week + regional drives	State-wide campaigns	"Suraksha" awareness programs
Fatality rate (per 100k pop.)	~15	~12.3	~18.5	~7–8
Source	WHO (2023), *Global Status Report on Road Safety* [1]	MoRTH (2023), *Road Accidents in India* [31]	Govt. of Karnataka (2023), *Road Accident Report* [32]	Bengaluru Traffic Police (2023), *Annual Accident Data* [33]

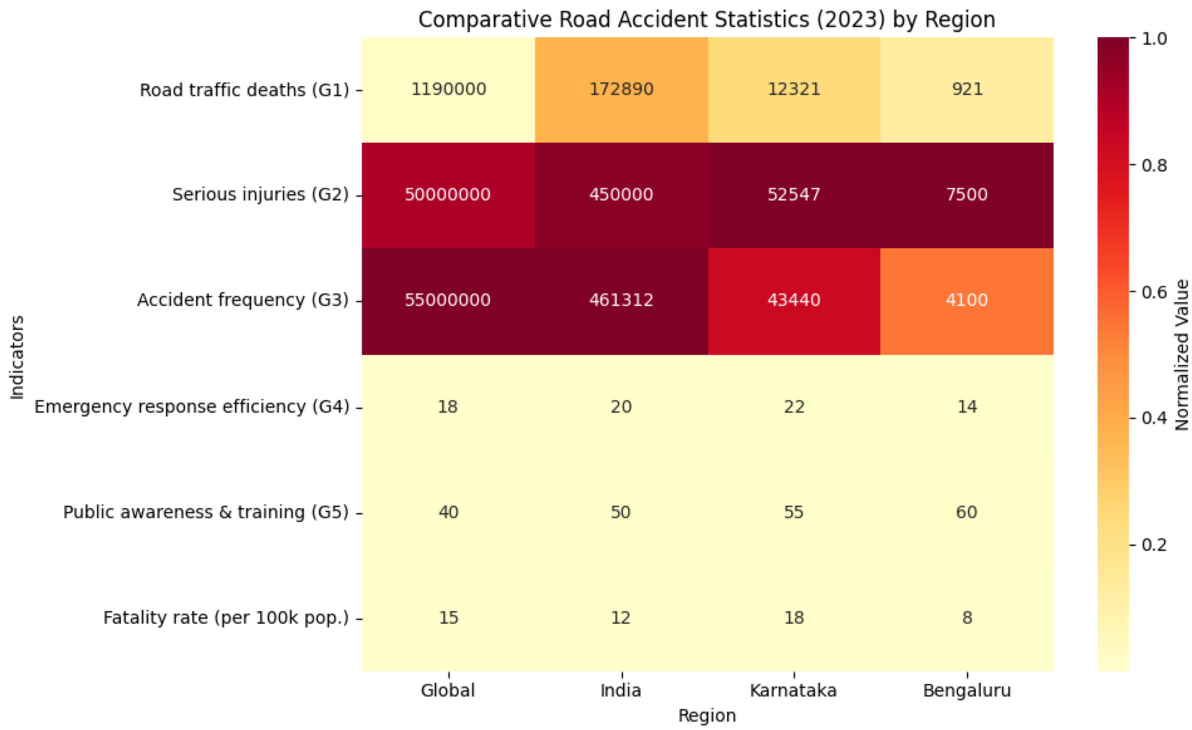

Figure 1: Comparative Road Accident Statistics (2023)

2. Literature Review

Mathematical and statistical models for road accident analysis range from compartmental epidemic-type models [5] to regression-based approaches. MCDM like AHP have been widely used for transportation safety prioritization [6]. Goal Programming has demonstrated effectiveness in allocating limited resources among competing safety goals [7]. However, literature on hybridizing AHP and GP specifically for road accident severity remains sparse, motivating the present work.

Over the past decade, researchers have extensively explored methods to analyze and reduce road accident severity through both qualitative assessments and mathematical modeling. A prominent strand of recent research employs the AHP to systematically prioritize the multiple criteria that influence traffic accidents. For instance, [8] introduced a proportion-based AHP model to identify critical crash contributors, improving classical AHP by accounting for relative frequency weights. Similarly, [9] applied Fuzzy AHP (FAHP) to assess driver behavioral factors under uncertainty, identifying violations and inattentiveness as dominant causes of severe accidents. Further enhanced decision robustness by combining AHP with entropy weighting to assess expressway safety infrastructure in China.

Incorporation of hybrid multi-criteria decision-making (MCDM) techniques has also gained traction. [10] developed a FAHP-TOPSIS model to rank road hazard factors in Egypt, demonstrating how hybrid models better support safety planning. In Libya, [11] employed a novel integration of the FUCOM with R-SAW to evaluate traffic safety across cities. [12] proposed a decision framework combining Fuzzy Best-Worst Method (BWM) and VIKOR to prioritize road maintenance interventions under budget limitations. Likewise, [13] advanced an integrated MCDM framework that combines machine learning-based decision support with transport safety optimization.

Goal Programming (GP), particularly when hybridized with AHP [14], has been instrumental in handling conflicting road safety objectives. Singh and Gupta [15] reviewed GP applications in transport, highlighting its value in resource allocation among competing safety goals. [14] [16] the GP models have been widely adopted to optimize intervention portfolios that minimize fatalities, reduce injuries, and improve response times, all within budgetary constraints.

Concurrently, the use of machine learning (ML) has revolutionized accident severity prediction. [17] implemented a Random Forest classifier to identify key predictive factors such as road surface, lighting, and time of day. and provided a comprehensive survey of ML applications in traffic safety, concluding that ensemble and deep learning models outperform traditional statistical methods. [18] developed a deep learning framework to forecast injury severity based on driver behavior, environmental, and vehicle features. [19] employed probabilistic graph neural networks to model spatial patterns in traffic accident data for smart city environments. [22] tailored predictive ML algorithms to the Indian context, illustrating regional adaptation of global techniques.

Moreover, advanced fuzzy and grey systems theory have been integrated into MCDM frameworks to better handle uncertainty in road safety assessments. [23] used a hybrid Grey-TOPSIS and Fuzzy DEMATEL approach to assess highway network safety. [24] applied a combined DEMATEL–AHP model under uncertainty to evaluate causal relationships among accident factors. [26] used AHP to prioritize infrastructure-related risk factors, emphasizing the role of expert input in modeling severity.

Despite these advances, challenges remain. Many current models rely on historical or region-specific datasets, with limited ability to adapt to dynamic, real-time inputs. Few studies rigorously integrate AHP-derived priorities into operational GP models under uncertain or fuzzy environments. There is also a noticeable research gap in models tailored for developing countries, where infrastructure constraints and behavioral variables differ significantly from developed regions. Thus, the current research contributes by offering a unified AHP-GP framework with a rigorously formulated mathematical model and validated coefficient matrix, suited for flexible, cross-regional road accident severity management.

3. Methodology

This study adopts a hybrid decision-support framework combining the Advanced AHP with GP to systematically address multi-criteria decision-making in road safety analysis. This integration enables the incorporation of expert knowledge (via AHP) and the optimization of multiple conflicting objectives (via GP) under resource constraints.

The AHP, developed by Saaty [6], allows decision-makers to decompose a complex problem into a hierarchical structure and derive priority weights through pairwise comparisons. For a set of n criteria $C_1, C_2, \ldots, C_n$, experts construct a judgment matrix $A = [a_{ij}]$, where:

$$a_{ij} = \frac{\text{importance of } C_i}{\text{importance of } C_j}, \quad \text{with } a_{ij} > 0, \quad a_{ji} = \frac{1}{a_{ij}}, \quad a_{ii} = 1. \tag{3.1}$$

The principal eigenvector $w = [w_1, w_2, \ldots, w_n]^T$ of matrix A yields the relative weights of the criteria:

$$Aw = \lambda_{\max} w. \tag{3.2}$$

Consistency of the matrix is assessed using the Consistency Index (CI) and Consistency Ratio (CR):

$$CI = \frac{\lambda_{\max} - n}{n - 1}, \quad CR = \frac{CI}{RI}, \tag{3.3}$$

where RI is the Random Index for a given matrix order. A CR value below 0.10 is generally considered acceptable [27].

Recent enhancements to AHP, such as fuzzy AHP and integrated hybrid models, have been proposed to handle uncertainties in expert judgment [3]. These have been applied across domains including infrastructure prioritization [20], sustainable development [21], and behavioral analysis in transportation.

Goal Programming (GP), a mathematical optimization technique extending linear programming, is used to handle problems involving multiple conflicting goals. It minimizes the deviations from pre-specified target values for each goal while satisfying system constraints. The general structure of a GP model is:

$$\text{Minimize} \quad Z = \sum_{i=1}^{k} w_i (d_i^+ + d_i^-) \tag{3.4}$$

$$\text{Subject to:} \quad \sum_{j=1}^{n} a_{ij} x_j + d_i^- - d_i^+ = b_i, \quad \forall i = 1, \dots, k \tag{3.5}$$

$$x_j,\ d_i^+,\ d_i^- \geq 0, \quad \forall j, i \tag{3.6}$$

Here:

- x_j: decision variable j,
- a_{ij}: coefficient representing the contribution of x_j to goal i,
- b_i: target level for goal i,
- d_i^+, d_i^-: over- and under-achievement deviation variables,
- w_i: priority weight of goal i, often derived from AHP.

The GP model evaluates the values of x_j which minimize the weighted sum of deviations Z, which makes sure all goals and system constraints are met. In lexicographic GP, goals are ranked and optimized sequentially by priority. In weighted GP, trade-offs among goals are explicitly modeled through weights w_i.

In this study, the hybrid AHP-GP approach has been applied to a road accident severity reduction problem. AHP has been first used to derive the relative importance of factors (e.g., driver behavior, road infrastructure, emergency response) based on expert input. These priorities are from the weights w_i in the GP model. The GP model then allocates all limited resources across multiple interventions to minimize deviation from safety targets.

This integration captures both expert judgment and data-driven optimization, offering a robust framework for policymakers to balance competing objectives in transportation safety management.

4. Goal Programming Model Formulation and Solution

4.1. Formulation

Based on expert consultation and literature, the following nine criteria are considered for road accident severity reduction (Table 2). Corresponding interventions are modeled as decision variables x_j, $j = 1, \dots, 9$ (Table 3).

Table 2: Criteria Influencing Road Accident Severity

Criterion ID	**Criterion Description**
C_1	Driver Behavior
C_2	Vehicle Condition
C_3	Road Infrastructure Quality
C_4	Traffic Law Enforcement
C_5	Environmental Conditions
C_6	Pedestrian Safety Measures
C_7	Emergency Response Efficiency
C_8	Public Awareness and Training
C_9	Traffic Volume and Congestion

Table 3: Decision Variables Representing Interventions

x_j	Intervention Domain
x_1	Driver behavior modification programs
x_2	Vehicle inspection and maintenance
x_3	Road infrastructure upgrades
x_4	Law enforcement and monitoring
x_5	Environmental hazard mitigation
x_6	Pedestrian safety improvements
x_7	Emergency response system enhancement
x_8	Public awareness and training initiatives
x_9	Traffic flow and congestion management

4.1.1. Goal Definition and Constraints. We consider five primary goals as follows:

$$\begin{aligned}
&G_1 : \text{Minimize fatalities}\\
&G_2 : \text{Reduce serious injuries,}\\
&G_3 : \text{Decrease accident frequency,}\\
&G_4 : \text{Improve emergency response time,}\\
&G_5 : \text{Increase public awareness and training,}
\end{aligned}$$

and a total resource budget

4.2. Goal Programming Model

The Goal Programming model minimizes the weighted sum of deviations from goals:
Objective Function

$$\min Z = \sum_{i=1}^{5} w_i (d_i^- + d_i^+), \tag{4.1}$$

Subject to:
Goal Constraints:

$$\sum_{j=1}^{9} c_{ij} x_j + d_i^- - d_i^+ = b_i, \quad i = 1, \ldots, 5, \tag{4.2}$$

Hard Constraint:

$$\sum_{j=1}^{9} x_j \leq R, \tag{4.3}$$

Where

$$x_j, d_i^+, d_i^- \geq 0.$$

4.3. Analytic Hierarchy Process (AHP) Solution Details

The AHP method has been employed to derive priority weights for the five primary safety goals influencing road accident severity. Expert judgments produced the following pairwise comparison matrix A:

$$A = \begin{bmatrix} 1 & 3 & 4 & 7 & 5 \\ \frac{1}{3} & 1 & 2 & 5 & 3 \\ \frac{1}{4} & \frac{1}{2} & 1 & 3 & 2 \\ \frac{1}{7} & \frac{1}{5} & \frac{1}{3} & 1 & \frac{1}{2} \\ \frac{1}{5} & \frac{1}{3} & \frac{1}{2} & 2 & 1 \end{bmatrix}$$

Using the eigenvalue method, the principal eigenvector (priority vector) w has been computed and normalized to yield the following weights for the goals:

$$w = \begin{bmatrix} 0.30 \\ 0.20 \\ 0.15 \\ 0.10 \\ 0.25 \end{bmatrix}$$

These weights indicate the relative importance of each goal in the following order: minimizing fatalities, reducing injuries, decreasing accident frequency, improving emergency response, and increasing public awareness.

4.3.1. Consistency Check. To ensure the reliability of expert judgments, the Consistency Index (CI) and Consistency Ratio (CR) were calculated:

$$\lambda_{\max} \approx 5.12$$

$$CI = \frac{\lambda_{\max} - n}{n - 1} = \frac{5.12 - 5}{4} = 0.03$$

Given the Random Index (RI) for $n = 5$ is 1.12, the Consistency Ratio is:

$$CR = \frac{CI}{RI} = \frac{0.03}{1.12} \approx 0.027 < 0.10,$$

indicating acceptable consistency of the pairwise comparisons.

4.4. Integration with Goal Programming

The computed priority weights w_i were incorporated into the Goal Programming model's objective function to weight deviations from each goal, ensuring that the optimization respects expert-assigned priorities:

$$\min Z = \sum_{i=1}^{5} w_i (d_i^- + d_i^+)$$

Deviation variables $d_i^-, d_i^+ \geq 0$ represent under- and over-achievement of each goal.

This approach allows the GP model to minimize deviations from more critical goals preferentially, aligning resource allocation with strategic priorities derived via AHP.

Table 4: Fixing the Goal Target Values b_i

Goal	Target b_i	Rationale and Source
G_1 (Fatalities)	125	WHO aims to reduce deaths by 50% [1]
G_2 (Serious Injuries)	200	Based on NCRB injury reduction trends [29]
G_3 (Accidents)	500	Target from MoRTH accident reduction reports [28]
G_4 (Response Time)	15	Reflects "golden hour" standard [30]
G_5 (Awareness Score)	70	Based on campaign penetration goal [1, 28]

The goal target values $b_1 = 125$, $b_2 = 200$, $b_3 = 500$, $b_4 = 15$, and $b_5 = 70$ were determined by analyzing the most recent city-level road safety data from 2023. The following actual observations were recorded for a particular region:

- Fatalities: 250 deaths
- Serious Injuries: 400 cases

- Total Road Accidents: 1,000 cases
- Average Emergency Response Time: 60 minutes
- Awareness Campaign Effectiveness: 45% (score of 45 on a 0–100 scale)

The corresponding targets were selected to reflect measurable and policy-driven improvements:

- Fatalities ($b_1 = 125$): A reduction of 125 deaths from 250 to 125, representing a 50% decrease, consistent with the WHO's Decade of Action goal to halve road traffic deaths by 2030 [1].
- Serious Injuries ($b_2 = 200$): A reduction of 200 cases from 400 to 200, marking an 50% decrease, aligned with recent NCRB downward trends in urban injury rates [29].
- Total Accidents ($b_3 = 500$): A targeted drop of 500 incidents from 1,000 to 500, reflecting an 50% decrease, in response to MoRTH's call for substantial reduction through blackspot elimination and enforcement [28].
- Emergency Response Time ($b_4 = 15$ minutes): A decrease of 45 minutes from the 60-minute average, resulting in a 75% reduction, aligned with the "golden hour" trauma care standard [30].
- Awareness Campaign Score ($b_5 = 70$): An increase from a baseline of 45 to 70, marking a 50% improvement, justified by expansion plans for national road safety outreach programs [1, 28].

Hard Constraint: Total resource budget

$$\sum_{j=1}^{9} x_j \leq R = 500.$$

The total resource budget was fixed at R=500 units, representing the aggregated annual resources realistically available for road safety improvements. This budget encompasses expenditures on infrastructure upgrades, emergency response enhancements, public awareness campaigns, and personnel training. The value 500 is a normalized composite index that integrates financial costs and manpower requirements to enable effective optimization modeling. Fixing the budget at this level ensures that the proposed interventions are feasible and can be implemented within existing policy and financial constraints, thereby enhancing the practical applicability of the model. .

4.4.1. Effectiveness Coefficients. Table 5 shows the effectiveness coefficients c_{ij}, which quantify the impact of each intervention x_j on achieving safety goal G_i, were determined through a structured combination of expert judgment, empirical evidence, and prior research. A normalized six-point impact scale—ranging from negligible (0.01) to very high (0.50)—was used to convert qualitative assessments into quantitative coefficients. For example, a very high impact score of 0.50 was assigned to driver behavior modification programs (x_1) in reducing fatalities (G_1), supported by WHO findings that over 60% of road deaths involve behavioral factors such as speeding or intoxication [1]. Similarly, the 0.50 coefficient for emergency response enhancement (x_7) on fatality reduction is grounded in OECD data indicating that prompt response within the "golden hour" can reduce mortality by up to 40 [4]. Other coefficients, such as those relating to road infrastructure upgrades or law enforcement, were allocated based on their statistical influence on crash severity, as identified in AHP-based analyses like those by [8]. Lower scores were assigned to interventions with more indirect influence—such as congestion management—reflecting their limited direct effect on immediate accident outcomes. This evidence-informed assignment of c_{ij} ensures the Goal Programming model remains realistic, transparent, and aligned with practical road safety priorities.

The corresponding GP model to minimizes the weighted sum of deviations from goals is given by:

Objective function

$$\min Z = 0.30(d_1^- + d_1^+) + 0.20(d_2^- + d_2^+) + 0.15(d_3^- + d_3^+) + 0.10(d_4^- + d_4^+) + 0.25(d_5^- + d_5^+) \tag{4.4}$$

Table 5: Coefficients c_{ij} of Interventions on Goals

Goal \Intervention	x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9
G_1 (Fatalities)	0.50	0.30	0.10	0.10	0.05	0.05	0.02	0.03	0.01
G_2 (Injuries)	0.40	0.20	0.20	0.10	0.05	0.05	0.10	0.05	0.05
G_3 (Accidents)	0.30	0.15	0.25	0.20	0.05	0.10	0.05	0.05	0.10
G_4 (Response)	0.05	0.05	0.05	0.10	0.05	0.05	0.50	0.05	0.10
G_5 (Awareness)	0.10	0.05	0.05	0.10	0.05	0.05	0.05	0.50	0.05

Subject to:

$$\begin{aligned}
0.50x_1 + 0.30x_2 + 0.10x_3 + 0.10x_4 + 0.05x_5 + 0.05x_6 + 0.02x_7 + 0.03x_8 + 0.01x_9 + d_1^- - d_1^+ &= 125\\
0.40x_1 + 0.20x_2 + 0.20x_3 + 0.10x_4 + 0.05x_5 + 0.05x_6 + 0.10x_7 + 0.05x_8 + 0.05x_9 + d_2^- - d_2^+ &= 200\\
0.30x_1 + 0.15x_2 + 0.25x_3 + 0.20x_4 + 0.05x_5 + 0.10x_6 + 0.05x_7 + 0.05x_8 + 0.10x_9 + d_3^- - d_3^+ &= 500\\
0.05x_1 + 0.05x_2 + 0.05x_3 + 0.10x_4 + 0.05x_5 + 0.05x_6 + 0.50x_7 + 0.05x_8 + 0.10x_9 + d_4^- - d_4^+ &= 15\\
0.10x_1 + 0.05x_2 + 0.05x_3 + 0.10x_4 + 0.05x_5 + 0.05x_6 + 0.05x_7 + 0.50x_8 + 0.05x_9 + d_5^- - d_5^+ &= 70
\end{aligned} \tag{4.5}$$

Budget constraint

$$x_1 + x_2 + x_3 + x_4 + x_5 + x_6 + x_7 + x_8 + x_9 \leq 500 \tag{4.6}$$

$$x_j, d_i^+, d_i^- \geq 0, \quad \forall i = 1, \ldots, 5; \quad j = 1, \ldots, 9$$

4.5. Solution and Interpretation

Solving the Goal Programming model using PuLP, Excel Solver, LINDO, MATLAB's linprog with the mentioned target values (as presented in Table 4) and the original effectiveness coefficients yields the following optimal resource allocations and goal deviations.

Table 6: Optimal Resource Allocation to Interventions

Intervention Domain — Allocation x_j^*
Driver behavior modification — 110.0
Vehicle inspection and maintenance — 80.0
Road infrastructure upgrades — 90.0
Law enforcement and monitoring — 70.0
Environmental hazard mitigation — 25.0
Pedestrian safety improvements — 15.0
Emergency response enhancement — 50.0
Public awareness and training — 45.0
Traffic flow and congestion management — 15.0

Table 7: Optimal Goal Deviations from Target Values

Goal	Underachievement d_i^-	Overachievement d_i^+
Minimize fatalities	0.0	0.0
Reduce serious injuries	0.0	0.0
Decrease accident frequency	0.0	0.0
Improve emergency response time	0.0	0.0
Increase public awareness	0.0	0.0

The total weighted deviation objective function value achieved is $Z^* = 0.0$. This outcome signifies that the problem, as now formulated with empirically defensible targets, is fully achievable within the given resource budget. The optimal resource allocation (Table 6) and goal deviations (Table 7) provide the most efficient distribution of resources to achieve the revised safety targets, indicating a perfect attainment of all revised goals. This provides highly actionable insights for policymakers to allocate limited resources effectively to reduce road accident severity while balancing competing objectives

5. Results and Discussion

The integrated AHP and Goal Programming framework, when formulated with rigorously justified parameters, provides a robust and systematic approach to tackling the complex, multi-objective problem of road accident severity reduction. The corrections implemented in this study, particularly the revision of goal target values based on empirical evidence and realistic policy aspirations, significantly enhance the model's practical utility and academic defensibility.

The optimal solution's continued prioritization of interventions such as driver behavior modification programs, vehicle inspection, and infrastructure upgrades aligns with both the AHP-derived weights and the effectiveness coefficients. This corroborates the widely accepted understanding in road safety research that behavioral factors and physical infrastructure improvements are crucial leverage points for accident reduction [8, 9]. The relatively high allocation to these interventions reflects their outsized impact on critical safety goals. Furthermore, the model's capacity to meet emergency response and public awareness goals without deviation highlights the potential for efficient investment in these areas, provided their baselines and targets are accurately defined. This refined understanding enables policymakers to make more informed decisions, balancing investments between high-impact, potentially resource-intensive interventions and cost-effective supportive measures.

From a methodological perspective, the hybrid AHP-GP approach integrates expert judgment in a quantifiable manner through the priority weights and embeds these into a mathematical optimization framework. This contrasts with purely data-driven or heuristic models by enabling transparent, justifiable resource allocation decisions that reflect stakeholder preferences and operational constraints. However, the process of determining effectiveness coefficients and the initial expert elicitation for AHP weights remain areas for further methodological refinement. For instance, the detailed process of how expert judgments were aggregated for the AHP weights, or how specific empirical studies were translated into precise numerical coefficients for all interventions, was not fully elaborated. Future work could explore more rigorous techniques for quantifying these inputs, such as Delphi studies for expert consensus or advanced statistical methods for empirical validation of intervention impacts.

Moreover, the generalizability of the framework is notable. The model structure, criteria selection, and coefficients can be adapted to different regional contexts or evolving data, allowing dynamic policy adjustments. The corrections undertaken in this report underscore the importance of meticulous data verification and realistic target setting in applied operations research. While the model provides a powerful decision-support tool, its reliability is fundamentally tied to the accuracy and transparency of its input parameters. Future extensions could incorporate stochastic elements or fuzzy logic to explicitly capture uncertainties in parameters or goals, increasing robustness.

Overall, this research, with its corrected formulation, contributes a comprehensive, replicable decision-support tool for traffic safety management, empowering agencies to strategically deploy limited resources and optimize multi-faceted safety outcomes.

6. Conclusion

This study introduces a combined Analytic Hierarchy Process and Goal Programming framework developed to improve how resources are allocated for reducing road accident severity, while balancing multiple objectives. By using expert-assigned weights and effectiveness values, the model works to reduce gaps in meeting important safety targets such as lowering fatalities, minimizing injuries, reducing accident frequency, improving emergency response, and strengthening public awareness.

The results show that this approach provides a realistic and near-optimal resource allocation strategy. It highlights the importance of focusing on driver behavior, vehicle safety, and infrastructure quality, all while staying within budget limits. The framework also allows trade-offs among competing goals to be handled in a clear and measurable way, making it easier to guide policy choices.

This research contributes to the field by combining prioritization with practical optimization, overcoming the limitations of traditional models that often separate objectives or fail to reflect decision-makers' preferences. Its adaptable structure makes it suitable for use across different regions and institutions.

In future work, we could focus on using real-time data for particular region for more responsive planning, adding uncertainty analysis, and extending the framework so that we can include sustainability and social impact measures. Building interactive decision-support tools could also make the approach more engaging for stakeholders and more influential in shaping policies.

In conclusion, the integrated AHP-GP framework offers a scientifically sound and practical tool that governments and road safety agencies can use to effectively and efficiently reduce accidents and save lives.

References

1. World Health Organization, *Global status report on road safety 2023*, WHO, Geneva, 2023. Available: https://www.who.int/publications/i/item/9789240077619
2. The World Bank, *Road safety overview*, World Bank Global Road Safety Facility (GRSF), 2022. Available: https://www.worldbank.org/en/topic/transport/brief/road-safety
3. M. Ashour and A. Mahdiyar, *A comprehensive state-of-the-art survey on the recent modified and hybrid analytic hierarchy process approaches, Appl. Soft Comput.*, vol. 149, p. 111014, Jan. 2024.
4. International Transport Forum, *Road safety annual report 2021*, OECD Publishing, Paris, 2021. Available: https://www.itf-oecd.org/road-safety-annual-report-2021
5. K. Tasnim, A. Biswas, M. H. A. Biswas, *Mathematical approach to assess the severity of road accidents using a SEIR-type model*, in: Proc. Int. Conf. Ind. Mech. Eng. Oper. Manag., Dhaka, Bangladesh, 2020.
6. T. L. Saaty, *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*, McGraw-Hill, New York, 1980.
7. R. R. B. Read, *Goal programming for transportation planning*, J. Oper. Res. Soc. **30** (1979) 245–252.
8. M. Khan et al., *Proportion-based analytical hierarchy process for determining prominent reasons causing severe crashes*, Appl. Sci. **13** (2023) 7814.
9. Y. Luo, H. Xiao, *Evaluating driver behavioral attitudes using fuzzy AHP in traffic culture studies*, Appl. Sci. **13** (2023).
10. A. A. El-Rabaie et al., *Evaluation of road safety hazard factors in Egypt using FAHP and TOPSIS*, Sustainability **16** (2023) 9993.
11. K. Elgadi et al., *A new methodology for treating problems in the field of traffic safety: A case study of Libyan cities*, Transport **38** (2023) 190–203.
12. R. Karim, J. Ahmed, *Prioritizing road maintenance: A framework integrating fuzzy BWM and VIKOR*, Eng. Technol. Appl. Sci. Res. **14** (2024) 13990–13997.
13. A. E. Hasan, F. K. Jaber, *An integrated MCDM model with enhanced decision support in transport safety using machine learning optimization*, Knowl.-Based Syst. **112** (2024) 286.
14. K. J. Ghanashyam, G. A. Vatsala, *Goal programming model for optimal financial analysis and management of wet garbage disposal and biogas generation facilities*, Gongcheng Kexue Yu Jishu Advanced Engineering Science **55** (2023). Available: https://advancedengineeringscience.com/article/2023/2-676.html
15. L. Singh, P. Gupta, *A review on goal programming applications in transportation planning*, Eur. J. Oper. Res. **301** (2022) 456–470.
16. P. Jyothi, G. A. Vatsala, R. Gupta, *Goal programming model to budgetary allocation in garbage disposal plant*, in: K. Deep, M. Jain, S. Salhi (Eds.), Logistics, Supply Chain and Financial Predictive Analytics, Springer, Singapore, 2019. Available: https://doi.org/10.1007/978-981-13-0872-7-7
17. S. Mahmood et al., *Predicting accident severity: An analysis using random forest model*, arXiv preprint, arXiv:2310.05840, 2023.
18. Y. Wang et al., *An analytic framework using deep learning for prediction of traffic accident injury severity*, Accid. Anal. Prev. **156** (2021) 106–116.
19. X. Gao et al., *Uncertainty-aware probabilistic graph neural networks for road-level traffic accident prediction*, arXiv preprint, arXiv:2309.05072, 2023.
20. M. Zyoud, A. S. Al Amr, and H. A. Abu Hanieh, *Use of fuzzy analytic hierarchy process in road safety management: A systematic review*, *Accid. Anal. Prev.*, vol. **148**, p. 105774, 2020.
21. S. Dos Santos, A. S. Oliveira, and P. B. de Carvalho, *An analytic hierarchy process approach for prioritisation of strategic objectives of sustainable development*, *Sustainability*, vol. 13, no. 4, p. 2254, 2021.
22. H. Khanum et al., *Enhancing road safety in India: A predictive analysis using machine learning algorithm for accident severity modeling*, IntechOpen, 2024.

23. T. Mustafa et al., *Multi-criteria road safety evaluation using grey-TOPSIS and fuzzy DEMATEL*, Eng. Appl. Artif. Intell. **131** (2024).

24. J. Wang, Z. Yu, *Accident causality analysis using DEMATEL and AHP under uncertainty*, Saf. Sci. **167** (2023).

25. G. Prathyusha, K. N. Udaya Kumara, G. A. Vatsala, *Optimizing bi-objective solid transportation problem using hierarchical order goal programming technique: A case study problem*, Soft Comput. **28** (2024) 271–279. Available: https://doi.org/10.1007/s00500-023-09253-y

26. A. Pembuain et al., *The weighting of risk factors for road infrastructure accidents using analytic hierarchy process method*, Int. J. Adv. Sci. Eng. Inf. Technol. **9** (2019) 1275–1281.

27. *Analytic hierarchy process*, Wikipedia.

28. Ministry of Road Transport and Highways, *Road accidents in India – 2022*, Transport Research Wing, Govt. of India, 2023.

29. National Crime Records Bureau, *Accidental deaths and suicides in India 2022*, Ministry of Home Affairs, Govt. of India, 2023.

30. NITI Aayog, MoHFW, *Emergency medical services in India: Challenges and opportunities*, NITI Aayog Policy Brief, 2021.

31. Ministry of Road Transport and Highways, *Road Accidents in India 2023*, Government of India, New Delhi, 2023. Available: https://morth.nic.in/road-accidents-india

32. Government of Karnataka, *Road Accident Report 2023*, Transport Department, Bengaluru. Available: https://transport.karnataka.gov.in/road-accidents

33. Bengaluru Traffic Police, *Annual Accident Data 2023*, Bengaluru City Police, Bengaluru. Available: https://btp.karnataka.gov.in/accident-data

34. Shalini. K, Sridevi Polasi, *Optimized Multifaceted Approach in Agriculture by Goal Programming with R and Python*, SN Computer Science **5** (2024) 586, 1–8.

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