Optimizing AHP for Autonomous Vehicle Risk Evaluation in Mixed Traffic

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***Abstract*—This paper proposes an optimization-based approach for the risk evaluation of Autonomous Vehicles (AVs) integration using the Analytic Hierarchy Process (AHP). A set of Key Performance Indicators (KPIs) is aggregated into a Global Traffic Indicator (GTI) to compare an AV scenario with a traditional traffic scenario. The methodology consists of two steps. In the first step, an AHP originally defined for conventional traffic evaluation is adapted to the AV scenario through a lexicographic optimization that adjusts the KPI weights while preserving consistency with the original pairwise judgments and reducing the influence of unfavorable indicators. In the second step, using the adapted weights, an optimization model identifies the minimum set of KPI improvements required for the AV scenario to outperform the traditional one. A case study shows that improvements in a limited number of KPIs are sufficient to obtain a GTI advantage for AV deployment.**

***Index Terms*—Autonomous Vehicles, Analytic Hierarchy Process, Key Performance Indicator, Global Traffic Indicator, Lexicographic Optimization**

I. Introduction

The progressive introduction of Autonomous Vehicles (AVs) in urban networks is expected to transform current traffic systems and intelligent mobility services, including autonomous logistics and delivery operations [1]. Potential benefits include improved road safety, reduction of congestion, reduced emissions, and enhanced accessibility for vulnerable road users [2]. At the same time, the integration of AVs into mixed traffic environments introduces new risks related to technologies, software reliability, and social acceptance [3]. To support planning and regulatory decisions, there is a growing need for quantifying and comparing the overall risk associated with AV and traditional transport scenarios across multiple dimensions [4] [5].

Key Performance Indicators (KPIs) are used to characterize the performance of transport systems from different perspectives, such as safety, efficiency, reliability, cost, environmental impact, and user acceptance. In the context of AV integration, relevant KPIs include accident rate, traffic queue length, decelerations, mechanical and software failures, and pollutant emissions [6]. However, since these indicators are heterogeneous, it is necessary to find a structured way to aggregate KPIs into a single measure that can be implemented to compare different scenarios.

The Analytic Hierarchy Process (AHP) is a widely used multi-criteria decision-making method for deriving relative weights of criteria from expert pairwise comparisons [7]. In transport and mobility planning, AHP has been applied to combine expert judgment with normalized KPI values [8], in order to compute indicators supporting risk and performance evaluation [9], as a Global Traffic Indicator (GTI), that summarizes the overall performance and risk level of a given scenario. Nevertheless, standard AHP assumes that the pairwise comparison matrix and the resulting weights remain fixed.

This paper proposes an optimization-based approach for the risk evaluation of AV integration in traffic environments, based on a GTI derived from an AHP. The approach considers two traffic scenarios: traditional scenario and an AV scenario. Both scenarios are characterized by a common set of KPIs organized into three main dimensions: hazard, vulnerability and exposure. Based on the original pairwise comparison matrix of AHP [10], the proposed approach refines the weights and quantifies the KPI improvements needed for AVs to achieve desirable GTI profile.

Although AHP is widely adopted in transportation risk evaluation, it depends on expert judgments and may therefore be affected by subjectivity, inconsistency, and inter-expert variability. Moreover, traditional AHP provides fixed weights that may not fully reflect the characteristics of emerging AV scenarios. The proposed approach addresses this limitation through a lexicographic optimization that preserves consistency with the original AHP structure while adapting KPI importance to the AV context.

The remainder of this paper is organized as follows. Section II recalls the AHP methodology and describes the KPI structure adopted for the risk evaluation based on the GTI. Section III presents the optimization models proposed for Step A and B. Section IV introduces the case study. Sections V and VI report and discuss the results obtained for Step A and B, respectively. Finally, Section VII concludes the paper and outlines directions for future research.

II. AHP and KPI-Based Risk Evaluation

The AHP is a multi-criteria decision-making methodology used to evaluate complex systems involving heterogeneous criteria. In the context of AVs integration, numerous technical, operational, environmental, and social factors must be considered simultaneously, making AHP an appropriate tool to evaluate priorities among the different KPIs.

AHP enables the decomposition of a decision problem into hierarchical levels and allows experts to express judgments on the relative importance of criteria, which are then translated into quantitative weights. These weights are subsequently combined with scenario specific KPIs values to compute the GTI.

This section summarizes the classical AHP procedure and describes the adopted KPI structure for the evaluation of AV risk.

A. Standard AHP Methodology

AHP relies on three fundamental steps [11]: problem decomposition, pairwise comparisons, and synthesis of priorities.

1) Problem decomposition: The first step consists of structuring the decision problem as a hierarchy that links the overall objective to intermediate categories and specific KPIs. In risk evaluation for AVs, the hierarchy typically includes:

- General objective: assess the global risk of the traffic scenario.
- Criteria: high-level dimensions such as hazard, vulnerability, and exposure.
- Sub-criteria/KPIs: measurable variables capturing accident rates, failure rates, environmental disturbances, and operational costs.

This hierarchical representation ensures transparency and consistency in the evaluation process [12].

2) Pairwise comparison: Once the hierarchy is defined, experts evaluate the relative importance of each pair of elements within the same level. This is achieved through pairwise comparisons using the Saaty numerical scale (1-9) [13], where:

- 1 indicates equal importance,
- > 1 indicates that element i is more important than element j,
- < 1 indicates the opposite, with $a_{ji} = 1/a_{ij}$ ensuring matrix reciprocity.

The resulting comparison matrix $A = [a_{ij}]$ is square of size $n \times n$, where n is the number of criteria or KPIs being evaluated. Diagonal elements satisfy $a_{ii} = 1$.

3) Synthesis of priorities: The local weights associated with each criterion are computed from the eigenvector of the comparison matrix or via equivalent normalization procedures. These weights quantify the contribution of each KPI to the global objective.

AHP is particularly suitable for AV risk evaluation because it combines qualitative expert judgments with quantitative performance indicators [14].

In this study, AHP is used to derive the baseline KPI weights for the GTI evaluation.

However, classical AHP produces fixed weights derived solely from expert judgment. In the proposed methodology, these weights constitute the starting point for Step A, where they are refined through optimization to account for scenario-specific KPI performance.

B. KPI structure for Risk Evaluation

The KPIs included in the AHP evaluation reflect the influencing risk associated with AV integration. The selected KPIs were derived from previous studies on AV risk assessment and from the IN2CCAM project framework, with the objective of covering the main dimensions involved in AV deployment, including safety, operational efficiency, technological reliability, environmental sustainability, economic impact, and social acceptance.

The indicators are grouped into three categories:

- Hazard: indicators related to accident rates, traffic efficiency, decelerations, and potential failures in mechanical, electronic, and software components.
- Vulnerability: focuses on factors that may compromise AV functioning due to external disturbances such as weather conditions affecting AV sensors and Internet connection disruptions.
- Exposure: economic, environmental, and societal indicators affecting users and stakeholders.

C. Global Traffic Indicator

These KPIs contribute to the evaluation of the GTI, a comprehensive metric used to assess the overall impact of AVs deployment on urban traffic. The GTI aggregates the KPI values of a given scenario into a single risk score. For a scenario characterized by normalized values y_k and weights derived from AHP w_k, the GTI is computed as:

$$GTI = \sum_k w_k y_k \tag{1}$$

Lower GTI values indicate better global performance.

III. Two-Step optimization Approach for Risk Evaluation

This section introduces the proposed optimization approach that extends the standard AHP methodology described before. Classical AHP produces a clear and consistent set of weights based on expert judgment, but these weights remain fixed across AV and traditional traffic scenarios. However, the baseline AHP structure mainly reflects risk priorities in conventional traffic systems. Therefore, Step A adapts this structure to the AV scenario while preserving consistency with the original pairwise comparisons.

To address this limitation, a two-step optimization approach is proposed. The first step refines the weight derived from the AHP while preserving consistency with the original pairwise comparison matrix. The second step determines the minimum improvements required on selected KPIs for the AV scenario in order to become preferable according to the GTI.

The proposed methodology is composed of the following steps:

- Step A: optimization of the AHP weights to reduce the influence of KPIs where the AV scenario performs worse than the traditional scenario, while remaining as close as possible to the original AHP structure.
- Step B: computation of the minimum feasible improvements on the unfavorable KPIs that allow the AV scenario to achieve an advantage over the traditional scenario in terms of GTI.

The two steps are sequential and complementary.

A. Step A: Optimization of AHP Weights

In Step A, the weights obtained from the standard AHP procedure [10] are refined through mathematical optimization. The objective is not to refine expert judgments, but to adjust the weights in a controlled way to better reflect the characteristics of the AV scenario.

Let $K = \{1, \ldots, n\}$ denote the set of KPIs, with n as the total number of KPIs considered. Let A_{ik} be the elements of the original AHP pairwise comparison matrix, where $A_{ii} = 1$ for all $i \in K$, and $A_{ik} = 1/A_{ki}$ for all $i \neq k$. Let y_k^{AV} represent the normalized value of KPI k for the AV scenario. A binary parameter $Worse_k$ identifies the KPIs for which the AV scenario performs worse than the traditional one.

$$Worse_k = \begin{cases} 1 & if \;\; y_k^{AV} > y_k^{TRAD} \\ 0 & \quad otherwise \end{cases} \tag{2}$$

The parameter W_{max} is a maximum admissible weight for a single KPI, introduced to avoid degenerate solutions and preserve a balanced weight distribution. Its value is chosen slightly above the maximum weight obtained from the original AHP analysis, ensuring flexibility in optimization while maintaining consistency with realistic AHP-based priorities. W_{max} is set to 1.25 times the maximum baseline AHP weight (rounded up). The factor 1.25 was selected to allow moderate flexibility around the baseline AHP weights while preventing unrealistic redistributions of importance.

The decision variables are the refined KPI weights w_k, which must satisfy the standard AHP normalization constraint and non-negative conditions. Additional deviation variables are introduced to quantify the violations of the ideal AHP relationships given by the original comparison matrix.

The refinement of the AHP weights is formulated as a lexicographic optimization problem, where objectives are optimized sequentially according to predefined priorities. Lower-priority objectives are optimized only among solutions that are optimal for higher-priority objectives. The three ordered objectives are:

1) minimize inconsistency with the original AHP structure, ensuring that the resulting weights remain anchored to expert judgments and preventing arbitrary favoring of the AV scenario;
2) minimize the total weight assigned to KPIs where the AV scenario is unfavorable, without arbitrarily altering the hierarchy;
3) minimize the resulting GTI of the AV scenario.

The resulting optimization problem produces a set of AHP weights that serve as input for Step B.

Parameters

$K = \{1, \ldots, n\}$	Set of KPIs
A_{ik}	Coefficients of the original AHP matrix $A_{ik} = 1/A_{ki} \; \forall i \neq k, A_{ii} = 1 \; \forall i \in k$
y_k^{TRAD}	Normalized value of KPI k for the traditional scenario
y_k^{AV}	Normalized value of KPI k for the AV scenario
$Worse_k$	Parameter equal to 1 if k performs worse in AV than in Traditional, 0 otherwise
W_{max}	Upper limit to the maximum weight allowed by KPI
wo_k	Original weight assigned to KPI k

Decision variables

$w_k \geq 0$	Weight assigned to KPI k
$u_{ik}^+ \geq 0, u_{ik}^- \geq 0$	Deviation variables measuring how much the ideal AHP relation is violated $w_i = A_{ik} \cdot w_k$ where $i \neq k$ and $i, k \in K$
$Incons$	Measure of inconsistency with the original pairwise judgments
$SumWBad$	Total importance given to criteria where AV is previously worse
GTI_{AV}	GTI in AV scenario using weights w_k

Decision variables functions

$$Incons = \sum_{i<k \in K} (u_{ik}^+ + u_{ik}^-) \tag{3}$$

In function (3), for each pair (i, k), $u_{ik}^+ + u_{ik}^-$ is the absolute deviation from the ideal AHP relation $w_i = A_{ik} \cdot w_k$. Measures the inconsistency with the original pairwise judgments. By minimizing $INCONS$, the model chooses w_k as close as possible to the AHP structure.

$$SumWBad = \sum_{k \in K : Worse_k = 1} w_k \tag{4}$$

The function (4) represents the total importance given to criteria where AV is previously worse. By minimizing $SumWBad$, the model tries to reduce the influence of KPIs that are unfavorable to AV, without breaking AHP consistency.

$$GTI_{AV} = \sum_{k \in K} w_k \cdot y_k^{AV} \tag{5}$$

The function (5) gives GTI of AV using new weights w_k.

Objective function

The problem is formulated as a three-level lexicographic minimization:

$$min(Incons, SumWBad, GTI_{AV}) \tag{6}$$

- Level 1: minimize inconsistency
- Level 2: among the equally consistent solutions, minimize the weight of worse KPIs.

- Level 3: among solutions that are still tied, favor weights that produce lower GTI_{AV}

Subject to

$$\sum_{k \in K} w_k = 1 \qquad w_k \geq 0, \; \forall k \in K \tag{7}$$

$$w_k \leq W_{max} \qquad \forall k \in K \tag{8}$$

(7) is the AHP constraint. (8) prevents degenerate solutions where a single KPI gets almost all the weight while others are almost zero. It keeps the resulting weights consistent with realistic AHP distributions.

$$\begin{aligned} u_{ik}^{+} &\geq w_i - A_{ik} w_k \\ u_{ik}^{-} &\geq A_{ik} w_k - w_i \\ \forall (i,k) &\in K, \; i < k \end{aligned} \tag{9}$$

Constraints (9) measure how far the optimized weights deviate from the ideal AHP relationship. Variables u_{ik}^{+} and u_{ik}^{-} calculate positive and negative deviations.

B. Step B: Required Improvements for AV Scenario

In Step B, the AHP weights obtained in Step A are considered fixed and given. The goal of this step is to determine the minimum improvements required in the KPIs where AV performs worse than the traditional scenario, so that the AV scenario becomes preferable according to the GTI.

Parameters

$K = 1, \ldots, n$	Set of KPIs
w_k^*	Fixed AHP weight of KPI k
y_k^{TRAD}	Normalized value of KPI k for the traditional scenario
y_k^{AV}	Normalized value of KPI k for the AV scenario
$Worse_k$	Parameter equal to 1 if AV performs worse than traditional in KPI k, 0 otherwise
ϵ	Required minimum advantage of AV over traditional in GTI
ρMax_k	Maximum allowed improvement for KPI k, expressing practical or technical limits
GTI_{TRAD}	GTI of the traditional scenario

Decision variables

ρ_k	Percentage improvements applied to KPI k in the AV scenario ($\rho_k \geq 0$)
GTI_{AV}^{new}	The new GTI for the AV scenario

Decision variables functions

$$GTI_{AV}^{new} = \sum_{k \in K} w_k^* \cdot y_k^{AV} (1 - \rho_k) \tag{10}$$

Function (10) is the new GTI for the AV scenario, after applying improvements ρ_k and using the fixed weights obtained in Step A.

Objective function

$$min \sum_{k \in K : Worse_k = 1} \rho_k \tag{11}$$

The objective function (11) minimizes the cumulative effort (in terms of percentage) required on the worse KPIs so that the AV becomes preferable according to the GTI.

Subject to

$$\rho_k \leq \rho Max_k \cdot Worse_k \qquad \forall k \in K \tag{12}$$

The constraint (12) set improvements only where AV is worse, and within realistic limits. If $Worse_k = 1$ it means that AV is worse than traditional in KPI k and, then, the model improve it, but at most up to its KPI-specific maximum percentage, reflecting realistic operational or social constraints.

$$GTI_{AV}^{new} \leq GTI_{TRAD} - \epsilon \tag{13}$$

Constraint (13) ensures that the set of improvements ρ_k is sufficient to make AV scenario GTI at least ϵ better than the traditional one. In Step B, GTI_{TRAD} denotes the reference GTI value of the traditional scenario obtained under the baseline AHP evaluation (w_0).

IV. Case Study

This section presents the case study used to validate the proposed AHP-optimization approach. The objective is to evaluate the integration of AVs by comparing this scenario with a traditional traffic scenario using KPIs. The case study is based on IN2CCAM project and a previous research [10].

The case study focuses on a mixed traffic environment in which AVs are integrated into a traditional traffic environment. There are two scenarios: traditional scenario and AV scenario.

In the traditional scenario, the traffic is composed exclusively of traditional vehicles. In the AV scenario, AVs are integrated in a conventional vehicle infrastructure.

The evaluation focuses on a set of 16 KPIs that include safety, environmental, economic, and social aspects. These KPIs are grouped into three main risk dimensions:

- Hazard: accident rates, traffic efficiency, decelerations, and technical failures.
- Vulnerability: weather conditions and Internet disruptions affecting AV operations.
- Exposure: economic, environmental, and social acceptance indicators.

Each KPI is normalized in the interval [0,1] (Table I). KPI normalization allows heterogeneous indicators with different physical meanings and scales to be aggregated consistently within the GTI formulation. Higher normalized values always correspond to worse performance or higher risk, ensuring coherence across all KPIs. Table I shows the normalized values of each KPI for both AV and traditional scenario and the

TABLE I
NORMALIZED VALUES AND ORIGINAL WEIGHT

KPI	y_k^{AV}	y_k^{TRAD}	$w0_k$
Accident rate	0.17	0.22	0.028
Accident severity	0.03	0.05	0.017
Traffic queue length	**0.5**	0.4	**0.058**
Waiting time at traffic lights	0.3	0.3	0.028
Decelerations	0.05	0.07	0.143
Technical failures	**0.03**	0.01	**0.139**
Mechanical failures	0.02	0.05	0.093
Software failures	**0.01**	0	**0.126**
Environmental factors	0	0	0.061
Internet disruptions	**0.01**	0	**0.04**
Production costs	**0.38**	0.03	**0.059**
Charging costs	**0.61**	0.2	**0.05**
Parking costs	0.25	0.25	0.03
Social acceptance	**0.6**	0.2	**0.088**
CO_2	0.2	1	0.02
NO_x	0.15	1	0.019

original weight assigned to each KPI. Values that are worse in the AV scenario compared to the traditional scenario are shown in bold.

The relative importance of the KPIs is initially determined through a standard AHP procedure. Expert surveys are conducted to perform pairwise comparisons among the KPIs using a reduced Saaty Scale [15]. The resulting pairwise comparison matrix is processed through the priority synthesis step to obtain normalized AHP weights.

These weights define the initial GTI values for both scenarios and provide the reference scale used to set W_{max} in Step A.

The proposed evaluation methodology is applied following a sequence of steps. First, the AHP pairwise comparison matrix is constructed. Next, baseline AHP weights are computed through the priority process and used to evaluate the initial GTI values for both the AV and traditional scenarios. After that, Step A is executed to refine the AHP weights using a lexicographic optimization with the objective of preserving consistency with the original AHP structure. Finally, the optimized weights are fixed and Step B is applied to determine the minimum KPI improvements required for the AV scenario to be better than the traditional one.

V. RESULTS STEP A

This section presents the results obtained from Step A, where a new set of AHP weights is computed for the AVs scenario. The objective of this step is to obtain a set of KPI weights that reduces the influence of criteria where the AV scenario performs worse than the traditional one.

W_{max} is set slightly above 1.25 times the maximum baseline AHP weight; in the case study we use $W_{max} = 0.20$.

Before analyzing the redistribution of weights, Table II reports the GTI values obtained under different configurations: (i) baseline AHP weights, (ii) optimized weights from Step A, and (iii) optimized weights combined with the KPI improvements obtained in Step B.

Table II summarizes the GTI values obtained under different configurations of the proposed methodology. The first row reports the GTI values computed using the original baseline

TABLE II
COMPARISON OF GTI VALUES UNDER DIFFERENT EVALUATION SETTINGS.

Evaluation setting	GTI_{TRAD}	GTI_{AV}	Δ (AV–TRAD)
Baseline AHP weights (w_0)	0.13053	0.17758	+0.04705
Step A optimized weights (w^*)	0.16608	0.16440	-0.00168
Step B improved AV scenario	0.16608	0.11703	-0.04905

TABLE III
RESULTS STEP A

KPI	Weight
Accident rate	0.04
Accident severity	0.013
Traffic queue length	0.054
Waiting time at traffic lights	0.027
Decelerations	0.161
Technical failures	0.121
Mechanical failures	0.081
Software failures	0.121
Environmental factors	0.081
Internet disruptions	0.04
Production costs	0.04
Charging costs	0.04
Parking costs	0.02
Social acceptance	0.081
CO_2	0.04
NO_x	0.04

AHP weights (w_0). Under these weights, the AV scenario exhibits a higher GTI than the traditional scenario, indicating a worse overall performance.

The second row presents the GTI values obtained after applying the lexicographic optimization of Step A. Using the optimized weights (w^*), the AV scenario achieves a slightly lower GTI than the traditional scenario. This result shows that a controlled and consistency-preserving redistribution of weights can influence the relative ranking of scenarios, while remaining compatible with the original AHP structure.

The third row reports the GTI value of the AV scenario after applying the KPI improvements identified in Step B. The resulting GTI demonstrates a clear advantage over the traditional benchmark.

Table III presents the optimized weights obtained from Step A for the AV scenario.

KPIs where AVs initially perform worse exhibit reduced weights, while safety-related KPIs maintain significant importance due to the consistency-preserving objective.

KPIs for which the AV scenario performs similarly or better than the traditional scenario exhibit stable or slightly increased weights, as they do not penalize the AV scenario in the GTI computation. A sensitivity analysis has been performed by varying W_{max} in the range $[0.18, 0.22]$. The same optimal solution was obtained for all tested values, with $Incons = 2.7038$, $SumWBad = 0.4966$, and $GTI_{AV} = 0.16436$. This indicates that the optimized weights are not sensitive to moderate variations of the maximum admissible KPI weight.

The optimized weights remain balanced, with no KPI reaching the upper bound W_{max}, confirming that the optimization avoids degenerate solutions and produces a controlled reallocation of importance. These optimized weights serve as the input for Step B.

TABLE IV
DATA ρMax_k

KPI	ρMax_k
Accident rate	0
Accident severity	0
Traffic queue length	0.5
Waiting time at traffic lights	0
Decelerations	0
Technical failures	0.4
Mechanical failures	0
Software failures	0.4
Environmental factors	0
Internet disruptions	0.4
Production costs	0.5
Charging costs	0.5
Parking costs	0.4
Social acceptance	0.3
CO2	0
NOx	0

TABLE V
RESULTS STEP B

KPI	ρ_k	New Normalized Value
Traffic queue length	50%	0.25
Production costs	46.62%	0.20
Charging costs	50%	0.31
Social acceptance	30%	0.42

VI. RESULTS STEP B

Step B computes the minimum KPI improvements required for the AV scenario to achieve an advantage with respect to the traditional reference. The optimization is carried out with a required advantage threshold set to $\epsilon = 0.02$, ensuring that the resulting AV scenario shows a clear improvement.

Table IV reports the maximum admissible improvement levels ρMax_k for each KPI, which reflect practical, technical, or social constraints. Improvements are allowed only on KPIs where the AV scenario initially performs worse than the traditional one.

Table V presents the optimal improvement levels ρ_k identified by the model together with the corresponding updated normalized KPI values, rounded to two decimals.

Results show that improvements are mainly required in traffic efficiency, charging costs, production costs, and social acceptance, highlighting their relevance for AV deployment.

All remaining KPIs do not require any improvement in the optimal solution.

Step B shows that the AV scenario can outperform the traditional one by focusing on a small set of key KPIs. These results confirm the value of the proposed approach by showing how multi-criteria risk evaluation can result in realistic improvements.

VII. CONCLUSIONS

This paper proposed an optimization-based approach for the risk evaluation of AV integration in traffic environments based on a GTI derived from an AHP. The approach combines expert assessment and mathematical programming to identify key KPIs and the improvements needed for AV deployment.

The first contribution, Step A, introduced a lexicographic optimization model to adjust the weights derived from the AHP while preserving consistency with the original pairwise comparison matrix. The proposed approach redistributes KPI importance in a clear and balanced way, reducing the influence of worse indicators.

Step B identifies the minimum set of KPI improvements required for the AV scenario to outperform the traditional one, showing that targeted improvements in a limited number of KPIs are sufficient to achieve a clear overall advantage.

The proposed methodology has some limitations, including the deterministic formulation of the GTI, the use of static KPI values, and the limited validation on a proof-of-concept case study.

Future work will focus on the integration of the proposed approach into a Decision Support System for AV deployment.

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