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Behavioral Adaptation and Risk Compensation in Horizontal Curve Crashes: A Multidimensional Accident Cost Rate Framework

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Research Article

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Abstract

Horizontal curve crashes represent a major road safety challenge worldwide. This study presents a multidimensional accident cost rate (ACR) framework for identifying high-risk horizontal curves using infrastructure, pavement friction, environmental conditions, and behavioral adaptation indicators. We developed a data-driven pipeline analyzing 2,563 km of Austrian rural roads over 12 years (2012–2023), combining police-reported crashes with RoadSTAR geometry/friction data and traffic exposure. The Accident Cost Rate (ACR) metric was applied at section and network levels, with a robust Hotspot_50 rule ($ACR_{section} > 1.5 \times ACR_{road}$) for prioritization. We employed bootstrap intervals, effect sizes, Spearman's correlation, and k-means clustering to derive actionable risk profiles. Among 3,333 curve crashes, we identified a behavioral adaptation paradox: highest accident costs occurred under dry pavement and daylight conditions. Curvature showed strong positive association with ACR ($\rho = 0.634$, $p < 0.001$), while AADT was negatively correlated ($\rho = -0.508$, $p < 0.001$). Counterintuitively, high friction ($\mu > 0.60$) correlated with increased ACR, suggesting risk compensation. Cluster analysis revealed four distinct risk profiles enabling targeted interventions. The framework provides transportation agencies with a transferable, computationally efficient tool for cost-weighted safety prioritization. Results demonstrate that behavioral adaptation can offset infrastructural safety gains, necessitating behavior-aware countermeasures in Vision Zero strategies.

1. Introduction

Traffic safety management has evolved significantly with the advent of computational methods and data-driven approaches to optimize infrastructure investments. While traditional safety science has extensively documented individual risk factors in isolation—such as road geometry, skid resistance, or weather conditions—Wallman and Åström [28] and FHWA [14] show that this fragmented approach fails to capture the synergistic effects that ultimately determine crash outcomes. Recent systematic reviews confirm that single-factor models substantially underestimate accident risk and cannot explain paradoxical findings where higher accident costs occur under seemingly safe conditions (Yang et al. [26]; Abdi et al. [1]).

This limitation becomes particularly evident when examining behavioral adaptation phenomena, where drivers systematically adjust their behavior based on perceived rather than objective risk levels. Emerging evidence from international studies underscores the necessity of integrated approaches: large-scale Norwegian analyses revealed unexpected safety effects of compound versus circular curves (Elvik and Strandvik Haugvik [12]), while machine learning applications demonstrate the value of prioritizing geometric features in safety assessment (Godumula and Ravi Shankar [17]). Complementary research identifies curve radius and approach speed as critical risk thresholds using decision-tree methods (Nadimi et al. [24]), and systematic reviews highlight the urgent need for explainable AI to improve accident prediction interpretability for safety practitioners (Lacherre et al. [21]).

The present study advances the field by introducing a novel multidimensional framework that simultaneously captures infrastructure, pavement, environmental, and behavioral parameters through the Accident Cost Rate (ACR) indicator. Our approach addresses a critical gap in contemporary road safety research by operationalizing behavioral adaptation mechanisms where risk compensation may outweigh infrastructural safety benefits—a phenomenon that remains insufficiently addressed in current literature despite its profound implications for safety investment efficiency.

This research is guided by three specific questions: (1) How do infrastructure, pavement, environmental, and behavioral parameters collectively influence accident risk in road curves? (2) To what extent does the Accident Cost Rate (ACR) effectively quantify socio-economic accident costs relative to exposure? (3) What comparative value do statistical and machine learning models offer for detecting high-risk curve sections?

Empirically, this research utilizes a comprehensive 12-year accident dataset (2012–2023) from Austrian rural roads, integrated with high-resolution infrastructure data from the RoadSTAR system (AIT [2]). The analytical approach combines traditional statistical methods with machine learning techniques, providing comprehensive insights through hybrid modeling that bridges explanatory and predictive analytics.

Although empirically grounded in Austrian data, the methodological framework is explicitly designed for international transferability. The integration of multidimensional predictors with advanced modeling contributes to global road safety research by delivering: (a) a replicable operationalization of behavioral adaptation assessment, (b) a validated multidimensional approach to curve safety evaluation, and (c) actionable insights for infrastructure management and Vision Zero strategies worldwide.

2. Literature Review

2.1. Road Geometry and Safety

Horizontal curves remain among the most safety-critical elements of the road network. In the United States, approximately 25% of all traffic fatalities occur on or near horizontal curves, and the crash rate on curves is nearly three times that on tangent sections (FHWA [14]). This dramatic overrepresentation highlights the strong influence of geometric design on crash risk, which has been further quantified through extensive studies on rural two-lane highways (Gooch et al. [18]).

Research consistently demonstrates that tight curve radii, insufficient transition curves, and inadequate superelevation are associated with elevated run-off-road crash risk (Cafiso et al. [7]; Maier et al. [22]). Detailed guidance on transition design and superelevation distribution is provided by Bonneson [5], while empirical studies confirm that small radii ($R < 200$ m) and abrupt alignment changes significantly increase both crash frequency and severity.

Furthermore, the interaction between horizontal and vertical geometry plays a critical role in crash causation. When steep grades coincide with horizontal curvature, the combined demand on lateral friction and stopping sight distance increases substantially, creating disproportionately high crash risks (Abdi et al. [1]). Inadequate cross-slope design can further destabilize vehicles, particularly under wet conditions, amplifying run-off-road risks (Zierke [31]; FHWA [13]).

Recent large-scale evidence from Norway reinforces these findings: based on nearly 64,000 curve segments, sophisticated accident models revealed that compound curves may be safer than simple circular ones, underlining the need for more nuanced geometric risk assessments that move beyond simplistic parameterizations (Elvik and Strandvik Haugvik [12]). Complementary approaches using machine learning on rural two-lane highways show that geometric factors such as sight distance and radius can be effectively prioritized for safety interventions (Godumula and Ravi Shankar [17]).

Together, these studies demonstrate that curve safety cannot be adequately understood by examining isolated parameters alone. A multidimensional framework is required that considers geometric, pavement, environmental, and behavioral factors simultaneously to capture the true complexity of crash risk in curves.

2.2. Pavement Friction and Safety Performance

Pavement friction plays a fundamental role in accident prevention, particularly in curve negotiation where lateral friction demands peak. A seminal study by Weinert and Vengels [30] identified low pavement grip as a significant factor in accident occurrence, especially on curved sections. Reduced friction values (< 0.35) increase accident probability by 27%, according to Cafiso et al. [7]. Cheng et al. [8] further analyzed the relationship between pavement roughness and crash risks, concluding that smoother road surfaces paradoxically lead to increased accident severity, as they encourage higher operating speeds that amplify crash consequences. The study by Buddhavarapu et al. [6] confirmed that lateral friction demand represents a more critical safety indicator than traditional longitudinal skid indices.

Recent advances in measurement techniques extend this perspective substantially. Macrotexture and microtexture analyses have shown that surface characteristics beyond simple skid resistance indices significantly affect crash risk. A systematic assessment of pavement skid resistance performance using fractal analysis of macrotexture confirmed that roughness indicators can serve as reliable predictors of safety-relevant friction (Hu et al. [20]). In practice, FHWA [14] now recommends network-level pavement friction management systems that integrate friction values, texture indices, and crash history to guide resurfacing priorities.

These insights underline that pavement-related risks cannot be reduced to isolated skid resistance thresholds. Instead, robust safety assessments require a multidimensional approach, combining friction indices, surface texture, and—crucially—driver adaptation effects. This aligns perfectly with the multidimensional framework of the present study, where skid resistance interacts dynamically with geometry, weather conditions, and behavioral proxies in explaining curve accident risk.

2.3. Traffic Volume, Exposure and Accident Cost Metrics

Traffic volume significantly influences accident cost rates through complex exposure mechanisms. While high-traffic roads tend to have lower accident frequency per vehicle-kilometer traveled, low-traffic roads experience disproportionately high accident costs due to more severe crashes (Bellini et al. [4]). This counterintuitive pattern was demonstrated in an analysis by Balck et al. [3], which identified low-volume, high-curvature roads as particularly high-risk sections deserving prioritized attention.

Correlation studies by De Oña and Garach [10] revealed that real driving speeds often exceed theoretical design speeds by 5–12 km/h, substantially increasing accident risks on curved sections. The 85th percentile speed (V85) frequently surpasses posted speed limits, leading to more run-off-road incidents (De Luca et al. [9]). Bellini et al. [4] further emphasized that real-time traffic monitoring and targeted speed enforcement are necessary to mitigate these risks, particularly on high-curvature, low-volume routes where speed discrepancies are most pronounced.

2.4. Hotspot Identification and Cluster-Based Risk Analysis

Traditional accident prediction models often fail to capture real-world crash patterns accurately, especially in curves where interactions between multiple factors dominate crash causation. To improve hotspot detection precision, advanced clustering techniques have been developed and validated (Cafiso et al. [7]). The hotspot classification method proposed by Vieten et al. [27] demonstrated that sections with high curvature and low traffic volumes exhibit disproportionately high accident costs despite lower exposure levels.

Further analyses underline the importance of exposure-based clustering for efficient resource allocation. Bellini et al. [4] identified hotspots on low-volume rural roads where accident costs per kilometer were significantly higher than on high-volume roads, suggesting different intervention strategies are needed for different road classes. The methodological shift towards data-driven methods is exemplified by Wang et al. [29], who successfully employed machine learning algorithms, including XGBoost and Random Forest, to identify high-risk curves on two-lane highways with superior precision compared to traditional statistical models.

This methodological progression is substantially advanced by the study of Moeinaddinia et al. [23], which explicitly compares a broad catalogue of machine learning algorithms for curve-related crashes. Cutting-edge studies confirm the added value of combining clustering with explainable AI techniques. For example, a systematic review highlighted that hybrid models using clustering plus explainable machine learning outperform classical black-box models in terms of interpretability for safety managers (Lacherre et al. [21]). Similarly, Nadimi et al. [24] used surrogate safety measures with decision-tree classifiers to identify hotspots in horizontal curves.

Furthermore, a recent evidence and gap map on global road safety interventions confirms that while infrastructure improvements are generally effective, their success is highly context-dependent and can

be influenced by behavioral adaptations (Goel et al. [19]).

3. Methods

3.1. Study Design and Data Framework

This study employed a comprehensive data-driven approach analyzing 2,563 kilometers of Austrian federal roads (B-roads) across two states over a 12-year period (2012–2023). The analysis incorporated 3,333 curve-related accidents, combining high-resolution infrastructure data from the RoadSTAR (AIT [2]) mobile laboratory with detailed accident records from official Austrian statistics. The methodological framework followed a systematic workflow for hotspot identification and risk assessment (Fig. 1 and Fig. 2), integrating multidimensional parameters through both statistical and machine learning approaches.

3.2. Data Collection and Integration

3.2.1. Accident Data

Curve-related accident data were obtained from Statistics Austria, focusing on police-reported injury accidents classified as curve-specific incidents (types 012, 013, 022, 023, 222, 223, 225, 226, 232, 242, 265, 266). The dataset spanned 2012–2023, providing comprehensive coverage of injury outcomes including fatalities, serious injuries, and slight injuries (see Appendix, Table A1). All accidents were precisely geolocated and matched to specific road segments using geographic information systems.

3.2.2. Infrastructure and Traffic Data

- **Road Geometry**: High-resolution alignment data captured via RoadSTAR system (AIT [2]), including curvature (degrees per kilometer), cross-slope (percentage), and longitudinal gradient (percentage). Measurement density ensured at least one data point every 10 meters.
- **Pavement Conditions**: Skid resistance measurements (μ-values) under varying surface conditions using standardized measurement protocols. Continuous friction data collected at network level with seasonal variations accounted for in the analysis.
- **Traffic Volume**: Annual Average Daily Traffic (AADT) data from state authorities and digital spatial information systems, with continuous monitoring stations providing robust exposure estimates.
- **Environmental Factors**: Precipitation, surface condition, visibility, and daylight data integrated from meteorological sources, allowing for detailed analysis of environmental influences on crash risk.

3.3. Geometric Standards

The analyzed B-roads conform to Austrian design standards (FSV [16]) with specified parameters:

- Minimum horizontal radius: 200 m

- Maximum longitudinal slope: 8%
- Cross slope range: 2.5% to 7%
- Design speed categories: 60–100 km/h depending on road class and terrain.

3.4. Accident Cost Rate (ACR) Framework

The core analytical metric, Accident Cost Rate (ACR), was calculated according to FGSV [15] guidelines, see Eq. (1):

$$ACR = \frac{AC \cdot 10^3}{AADT \cdot L \cdot 365 \cdot t} \quad \text{Eq. (1)}$$

Where:

- AC Accident costs (€) based on standardized cost valuations
- AADT Average annual daily traffic (vehicles/24h)
- L Road section length (km)
- t Observation period (years)

The accident cost rate of roads (ACR_{road}) was determined based on the total road length of the respective road as the section length L [km]. A one-year period was chosen for the observation period [a] to ensure comparability. The following considerations were implemented in the analysis:

- All roads were divided into 1.0 km-long sections, as the AIT [2] calculated the rolling curvature for these 1,000 m sections for this study.
- The accident cost rate per section ($ACR_{section}$) was calculated specifically for the 1.0 km sections, based on the Annual Average Daily Traffic (AADT), for a one-year period, and per 1.0 km section length.
- The accident cost rates for the respective roads (ACR_{road}) were calculated for the period from 2012 to 2023 (12 years), using the average AADT value over these 12 years, relative to the length of each road.
- If the accident cost rate of a section ($ACR_{section}$) is higher than the accident cost rate of the respective road (ACR_{road}) in which the section is located, the section is classified as a high-accident-risk section

3.5. Hotspot Identification Protocol

Sections were classified as high-risk hotspots using a conservative threshold:

$$ACR_{Section} > 1.5 \times ACR_{Road} \quad (2)$$

This Hotspot_50 criterion ensured identification of sections where accident costs significantly exceeded network averages, providing a robust basis for prioritizing safety interventions. Comparative analysis confirmed Hotspot_50's superior specificity over alternative thresholds (e.g., Hotspot_40). The bootstrap confidence intervals for Hotspot_40 and Hotspot_50 produced the following results: Hotspot_50 has a narrower distribution, as its confidence intervals are more centered around the mean range. In contrast, Hotspot_40 shows a broader spread of values, meaning it may be slightly more lenient. For this analysis, we focus on the most dangerous sections. Therefore, Hotspot_50 is chosen for further analyses, as it provides a more practical and realistic representation (see Appendix, Table A2 and Table A3). However, Hotspot_40 is mentioned as an alternative approach for less conservative applications.

Effect sizes (Cohen's d) were calculated to measure the strength of differences between hotspots and non-hotspots. For rolling curvature, Cohen's d was − 0.169, indicating a small effect. For the number of curve-related accidents, it was − 0.938, indicating a large effect, meaning hotspots experience significantly more accidents. For traffic volume (AADT), it was − 0.105, indicating no significant effect. Descriptive statistics (see Appendix, Table A4) showed wide ranges for all key variables, confirming substantial heterogeneity across road sections, with some sections generating exceptionally high accident costs.

3.6. Spearman's Correlation

Spearman's correlation analysis (see Appendix, Table A5) was employed to examine relationships between key variables due to the non-normal distribution of several parameters. This non-parametric approach provides robust insights into monotonic relationships without distributional assumptions.

3.7. Cluster Analysis

3.7.1. Hierarchical Cluster Analysis

Hierarchical cluster analysis using the Ward method was conducted to identify natural groupings within the dataset. The dendrogram (Fig. 3) and the Elbow Criterion (Fig. 4) were used to determine the optimal number of clusters. The analysis suggested initial mergers of similar elements, with later mergers showing sharply increasing coefficients, indicating a heterogeneous sample. The Elbow Point was visible at a cluster count of 5.

3.7.2. K-Means Cluster Analysis

The K-Means Cluster Analysis was used to divide the data into distinct, interpretable groups. After hierarchical analysis suggested 5 clusters, K-Means was tested with 4, 5, and 6 clusters. The 4-cluster solution provided the most distinct and interpretable risk profiles with practical significance for infrastructure management (Table 1).

Table 1
Four-Cluster Model (Hotspot_50)

	Cluster			
	1	2	3	4
Rolling Curvature at Section Midpoint [°/km]	100.3	284.6	256.8	170.2
$ACR_{section}$ [€/1,000 veh-km]	22.081	3.066	19.298	6.485
ACR_{road} [€/1,000 veh-km]	1.386	2.299	10.778	3.175
Number of Accidents 2012–2023	3.000	2.429	2.569	2.738
Annual Average Daily Traffic AADT [veh/24h] 2012–2023	16,224	15,559	3,765	9,690

- **Cluster 1**: Highly burdened sections with increased accident cost rate (ACR) and high traffic volume, representing major routes with significant safety challenges.
- **Cluster 2**: Curvy, low-traffic secondary roads with low ACR despite high curvature, suggesting effective driver adaptation to visibly hazardous conditions.
- **Cluster 3**: Accident-prone, low-traffic sections with high risk despite low traffic volume, indicating critical infrastructure deficiencies.
- **Cluster 4**: Balanced risk segments with moderate traffic load and moderate accident costs, representing efficiently operating infrastructure.

4. Results

4.1. Hotspot Identification and Behavioral Paradox

The Hotspot_50 analysis revealed that 51% of road sections (534 of 1,048 segments) exhibited significantly elevated accident cost rates, with a pronounced concentration in high-curvature (> 200°/km), low-traffic (< 5,000 vehicles/day) segments. This distribution underscores the substantial proportion of the network requiring safety interventions and highlights the economic significance of curve-related accidents.

Most notably, we observed a central paradox with profound implications for safety management: the highest accident cost rates occurred not during objectively hazardous conditions (snow, ice, poor visibility) but under ostensibly safe conditions—dry pavements and daylight hours. This pattern strongly suggests that driver behavior, rather than environmental challenges, plays the dominant role in severe crash causation on curved sections.

4.2. Multidimensional Risk Relationships

Correlation analysis confirmed significant relationships between key parameters and accident costs, revealing the complex interplay of factors influencing curve safety. Curvature density showed a strong

positive association with ACR ($\rho = 0.634$, $p < 0.001$), confirming the fundamental importance of geometric design in crash risk. This geometric influence was substantially moderated by traffic exposure, as evidenced by the pronounced negative correlation between AADT and ACR ($\rho = -0.508$, $p < 0.001$), suggesting that higher traffic volumes may induce more cautious driving behavior.

A particularly counterintuitive finding emerged regarding pavement friction: a positive correlation was identified between high pavement friction ($\mu > 0.60$) and elevated ACR. This relationship contradicts conventional safety engineering wisdom but aligns with behavioral adaptation theories, where improved road surface conditions may enable higher operating speeds and more aggressive maneuvering, ultimately increasing crash severity.

4.3. Cluster-Based Risk Profiling

Cluster analysis identified four distinct risk profiles with characteristic patterns that enable targeted intervention strategies:

- **Cluster 1** (High-Risk/High-Volume): Characterized by high curvature density and elevated ACR despite moderate geometric challenges, these sections represent major routes where behavioral interventions and speed management may yield significant safety benefits.
- **Cluster 2** (High-Curvature/Low-Risk): Exhibiting the highest curvature values but lowest ACR levels, these sections demonstrate that geometric challenges alone do not determine crash risk when drivers adequately adapt their behavior to visible hazards.
- **Cluster 3** (High-Risk/Low-Volume): Representing the most critical safety concern, these sections combine moderate-to-high curvature with very high ACR values despite low traffic volumes, suggesting substantial infrastructure deficiencies requiring geometric improvements.
- **Cluster 4** (Moderate-Risk/Moderate-Volume): Displaying balanced characteristics across all parameters, these sections represent efficiently operating infrastructure that may serve as benchmarks for network performance standards.

The clustering approach demonstrates how multidimensional risk assessment moves beyond simple crash frequency counting to incorporate cost-based prioritization and behavioral insights, enabling more efficient resource allocation for safety improvements.

4.4. Temporal and Environmental Patterns Paradox

Analysis of accident distribution across environmental conditions revealed striking patterns that further support the behavioral adaptation hypothesis. Contrary to conventional expectations, the majority of high-cost accidents occurred during daylight hours (72%) and under dry pavement conditions (64%), while adverse conditions such as rain, snow, and darkness accounted for a disproportionately small share of total accident costs. This distribution suggests that drivers successfully compensate for visible hazards but may overestimate their capabilities under ostensibly safe conditions, leading to more severe consequences when errors occur.

5. Discussion

5.1. Interpretation of Key Findings

The central paradox driving this research—higher accident costs under ostensibly safe conditions—strongly suggests behavioral adaptation mechanisms, where drivers compensate for perceived safety through increased risk-taking. These finding challenges conventional safety paradigms that focus primarily on objective hazard reduction and demonstrates the non-trivial nature of behavioral adaptation effects, potentially explaining why improved infrastructure alone may not yield expected safety gains. Our results align with risk homeostasis theory while providing empirical evidence specific to horizontal curve design and operation.

The counterintuitive positive correlation between high pavement friction ($\mu > 0.60$) and elevated ACR merits particular attention from both theoretical and practical perspectives. While conventional safety models would predict improved friction to reduce crash likelihood, our findings suggest potential risk compensation behaviors where drivers utilize available friction through speed increases or more aggressive maneuvering. This phenomenon aligns with behavioral adaptation theories observed across transportation domains and represents a significant contribution to understanding why safety investments sometimes yield disappointing returns. The implications extend beyond curve design to broader pavement management strategies, suggesting that friction improvements should be coupled with complementary measures addressing driver behavior.

5.2. Implications for Safety Management

Our findings challenge conventional safety paradigms in several crucial aspects that demand reconsideration of current practice. First, the persistence of high accident costs under "safe" conditions necessitates a fundamental shift in how we define and respond to risk in transportation systems. Rather than focusing exclusively on objective hazards, effective safety strategies must account for the subjective risk perceptions that drive behavioral adaptation. This suggests incorporating behavioral insights into infrastructure design standards and management practices.

Second, the complex interaction between geometric design, pavement properties, and behavioral responses highlights the limitations of single-dimension interventions. Successful safety management requires integrated approaches that address both infrastructure deficiencies and the behavioral mechanisms they trigger. For run-off-road crashes specifically, infrastructure countermeasures such as forgiving roadsides, enhanced delineation, shoulder rumble strips, and barrier upgrades are well documented in practice guidelines (e.g., DVR [11]), but their effectiveness may be enhanced when combined with behaviorally-informed speed management and driver feedback systems.

Finally, the ACR framework provides a transferable methodology for agencies seeking to implement evidence-based safety prioritization in resource-constrained environments. By focusing on socio-economic costs rather than simple crash counts, this approach enables more strategic resource

allocation and supports the progressive implementation of Vision Zero principles through cost-effective intervention targeting.

It is important to emphasize that several of our findings are non-trivial and counterintuitive, directly challenging established assumptions in road safety research. Most notably, we observe a positive association between high pavement friction ($\mu > 0.60$) and increased accident costs—contradicting the conventional expectation that improved surface quality inherently enhances safety. This pattern strongly supports the hypothesis of a risk compensation effect, whereby drivers consume available safety margins through higher speeds. Similarly, the behavioral-adaptation paradox—higher accident costs under ostensibly safe conditions (dry pavement, daylight)—is far from obvious and indicates that subjective risk perception may outweigh objective hazard levels in crash causation, with important implications for safety education and communication strategies.

5.3. Novel Contributions in an International Context

This study advances the state of the art in three complementary ways that bridge methodological innovation and practical application:

(1) Conceptual Advancement: We operationalize behavioral adaptation and risk compensation mechanisms in horizontal curves through a cost-based safety indicator (ACR) and demonstrate a reproducible behavioral-adaptation paradox. This reveals a fundamental mechanism by which infrastructure improvements can be partially or completely offset by adaptive driver responses, explaining why safety investments may not deliver expected benefits.

(2) Methodological Innovation: We integrate a cost-weighted hotspot rule ($ACR_{section} > 1.5 \times ACR_{road}$) with robust evidence checks and hybrid analytics combining traditional statistics with machine learning approaches. Unlike frequency-driven methods common in current practice, our framework prioritizes segments by socio-economic risk burden and explicitly incorporates behavioral adaptation as an explanatory layer, yielding interpretable risk typologies with direct management relevance.

(3) Empirical Contribution and Transferability: Using a high-resolution 12-year dataset from Austria, we demonstrate a portable analytical pipeline designed to produce comparable results across diverse data environments. The methodology requires only basic infrastructure and crash data available in most jurisdictions, facilitating international adoption and comparative analysis.

Positioning our contribution relative to prior work: Whereas earlier studies primarily model curve safety via isolated geometric parameters, simple crash counts, or black-box machine learning approaches, our approach embeds behavior-proximal mechanisms within a cost-based prioritization framework and provides interpretable cluster profiles that directly support decision-making processes in infrastructure management.

5.4. Practical Applications and Implementation Pathways

The ACR framework developed in this study provides a transferable methodology for prioritizing safety investments across diverse geographical and institutional contexts. While our empirical application focused on Austrian rural roads, the analytical approach is inherently portable and adaptable. The core workflow requires minimal adaptation: road networks can be segmented into manageable units using available GIS data, curvature proxies derived from design documents or mobile mapping, and accident cost rates estimated using jurisdiction-specific valuations. This flexibility enables agencies with varying data resources and institutional capacities to implement the approach and allocate limited budgets toward sections offering the greatest safety returns.

Many road authorities operate under conditions of limited data availability, particularly in developing countries or regions with decentralized infrastructure management. The proposed framework is explicitly designed to yield reliable prioritizations even under such circumstances through stability tests, robust estimation methods, and sensitivity analyses that help mitigate the effects of data missingness or quality issues. The framework can also be effectively combined with surrogate safety measures and open-source datasets where traditional crash records are incomplete or unavailable.

6. Limitations and Future Research

While this study provides a robust multidimensional framework for curve safety assessment, several limitations warrant acknowledgment to guide appropriate interpretation and future research directions. The Austrian context, despite its high-quality data and well-documented infrastructure, may limit immediate transferability to regions with different design standards, driver behavior patterns, or crash reporting practices. Our focus on curve-specific accidents, while methodologically justified for isolating geometric effects, excludes potential interactions with tangent sections and transition zones that may influence overall route safety.

Methodologically, while the Hotspot_50 approach proved effective for our dataset, comparative validation against Empirical Bayes methods or network-based clustering approaches could strengthen findings and provide additional robustness checks. The infrastructure-focused analysis, while comprehensive in geometric and pavement parameters, omits potentially significant human factors (e.g., driver age, experience, distraction) and vehicle characteristics (e.g., safety systems, stability control) that influence crash risk on curves.

The 12-year observation period, while substantial for capturing intermediate-term trends, assumes relative risk stability across the study period and may not fully capture evolving trends from changing vehicle fleets, mobility patterns, or climate impacts. Future research should address these limitations through: (1) integration of naturalistic driving data and computer vision techniques for enhanced behavioral insights; (2) validation of the framework across diverse international contexts with varying design standards and driver populations; (3) development of dynamic risk models incorporating real-time environmental and traffic factors; and (4) evaluation of countermeasure effectiveness through controlled implementation studies that isolate infrastructure and behavioral effects.

Additionally, future work could explore the integration of emerging data sources such as probe vehicle data, crowdsourced friction measurements, and advanced weather modeling to enhance the temporal and spatial resolution of risk assessments. The application of explainable AI techniques could further improve model interpretability while maintaining predictive performance, bridging the gap between black-box machine learning and practical safety management needs.

7. Conclusions

This study demonstrates the Accident Cost Rate (ACR) as a powerful socio-economic indicator for prioritizing road safety interventions internationally. Our analysis reveals a critical paradox with profound implications for safety management: the highest accident costs occur not during objectively hazardous conditions but under ostensibly safe circumstances—dry pavement and daylight—highlighting the substantial role of behavioral adaptation in crash causation. This finding necessitates a fundamental reconsideration of conventional safety engineering approaches that focus primarily on hazard elimination without addressing behavioral responses.

The multidimensional framework—integrating infrastructure, environmental, and behavioral parameters with hybrid statistical and machine-learning approaches—provides a transferable methodology for identifying high-risk sections across diverse contexts. Key findings indicate that high curvature density

combined with low traffic volume creates disproportionately hazardous conditions, while improved geometric design significantly reduces accident costs when implemented with consideration of likely behavioral responses.

For transportation authorities worldwide, this research offers actionable strategies: prioritize safety investments on tight curves ($R < 200$ m) and low-volume, highly curved segments where risk is concentrated; implement behavior-aware interventions that address risk-compensation mechanisms through integrated infrastructure and education approaches; and adopt cost-based hotspot identification for optimized resource allocation that maximizes safety return on investment.

Future research should expand this work through explainable-AI applications that enhance model interpretability, international validation across diverse geographic and cultural contexts, and dynamic risk modeling that incorporates real-time environmental and traffic conditions. These directions align with global evidence on the effectiveness of road safety interventions and will further strengthen behavior-sensitive safety management approaches supporting Vision Zero objectives worldwide.

These results support the Vision Zero philosophy by unifying costs, infrastructure, and behavioral adaptation within an interpretable, prioritizable framework. The methodology is internationally scalable, enabling evidence-based, economically prioritized interventions across diverse data environments and institutional settings. By addressing both the engineering and behavioral dimensions of curve safety, this approach moves beyond traditional single-dimension strategies toward more comprehensive and effective safety management.

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Figures

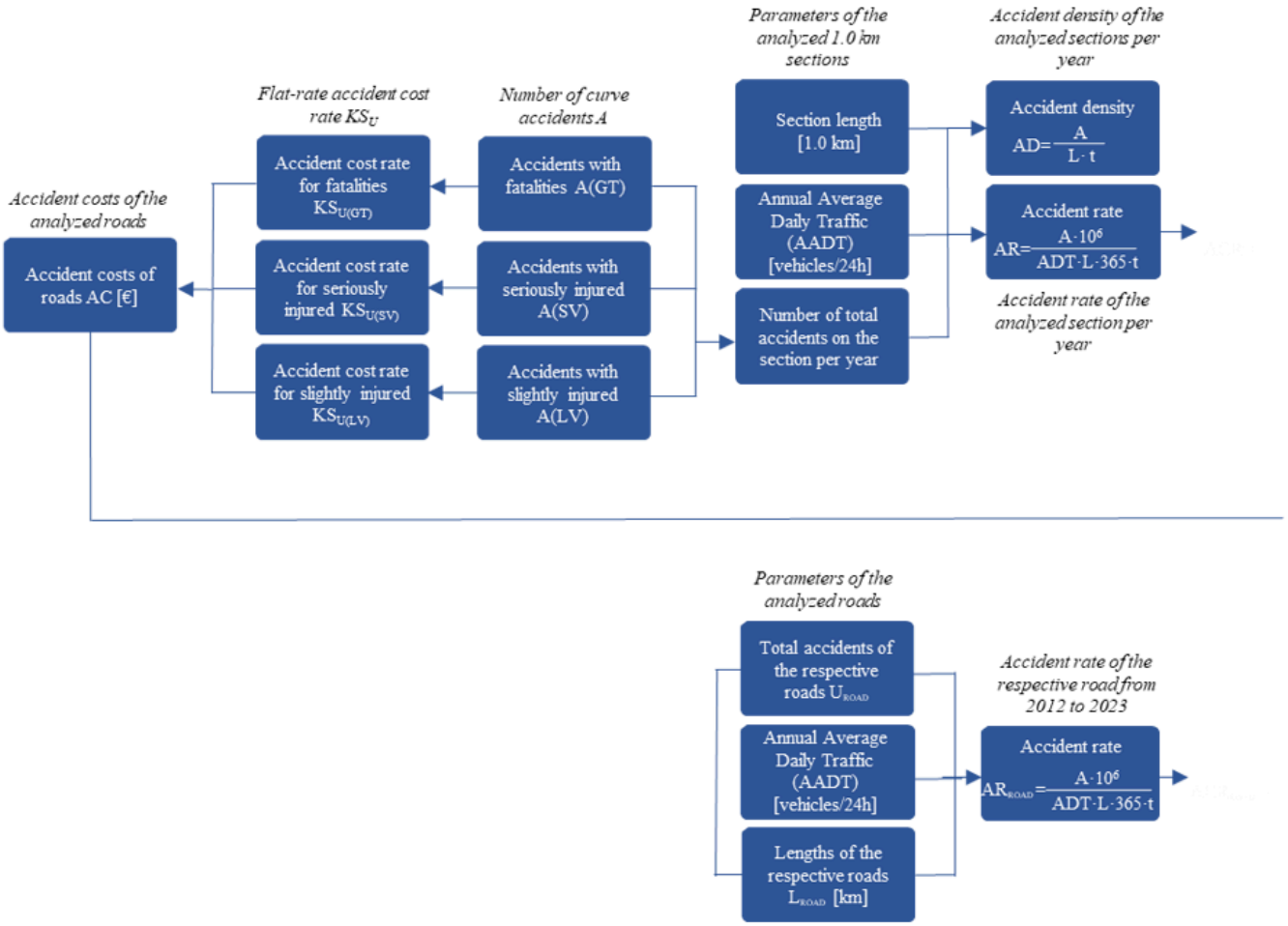


Figure 1

Flowchart (Workflow) for the Analysis of Accident Hotspots – First Part

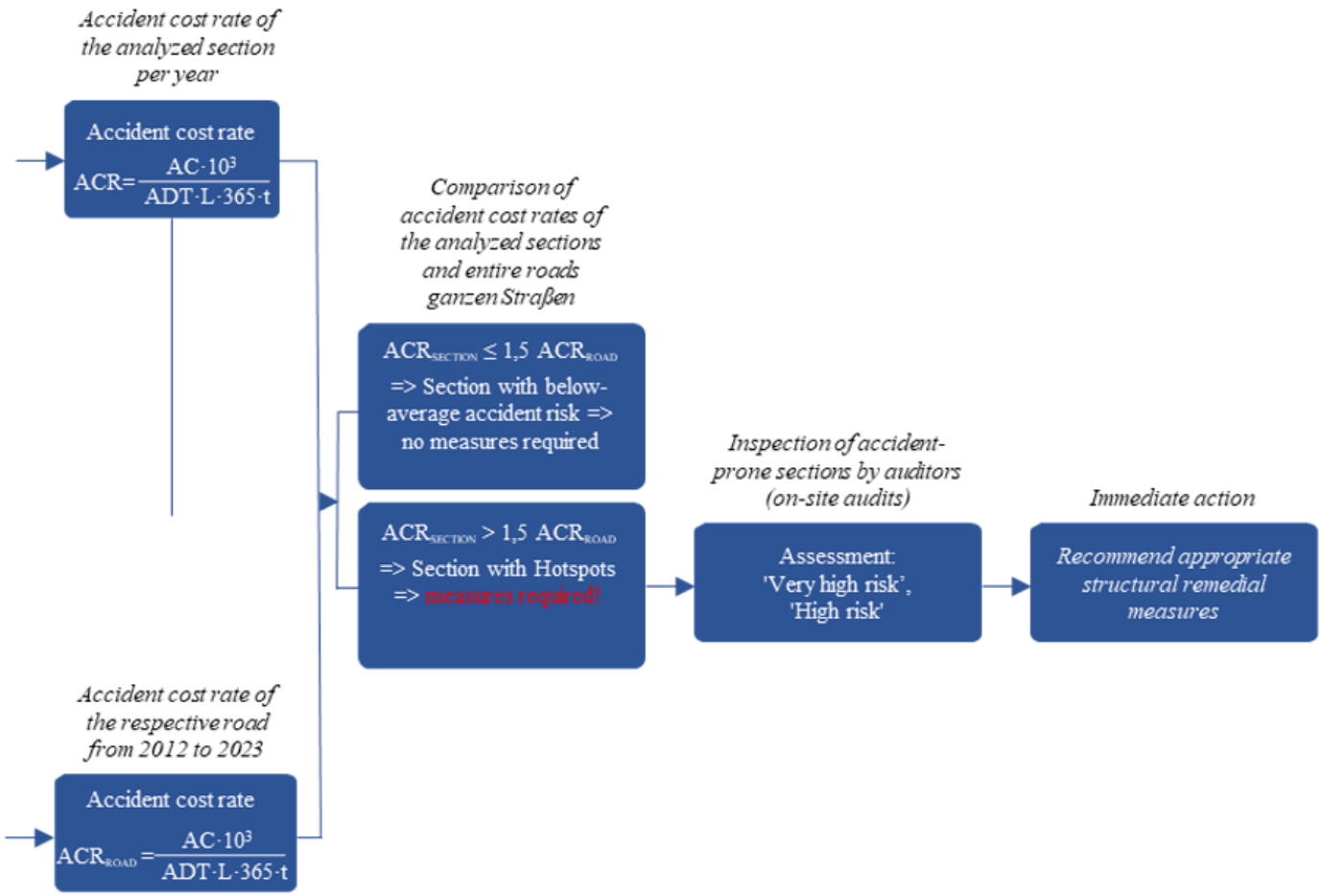


Figure 2

Flowchart (Workflow) for the Analysis of Accident Hotspots – Second Part (Continuation)

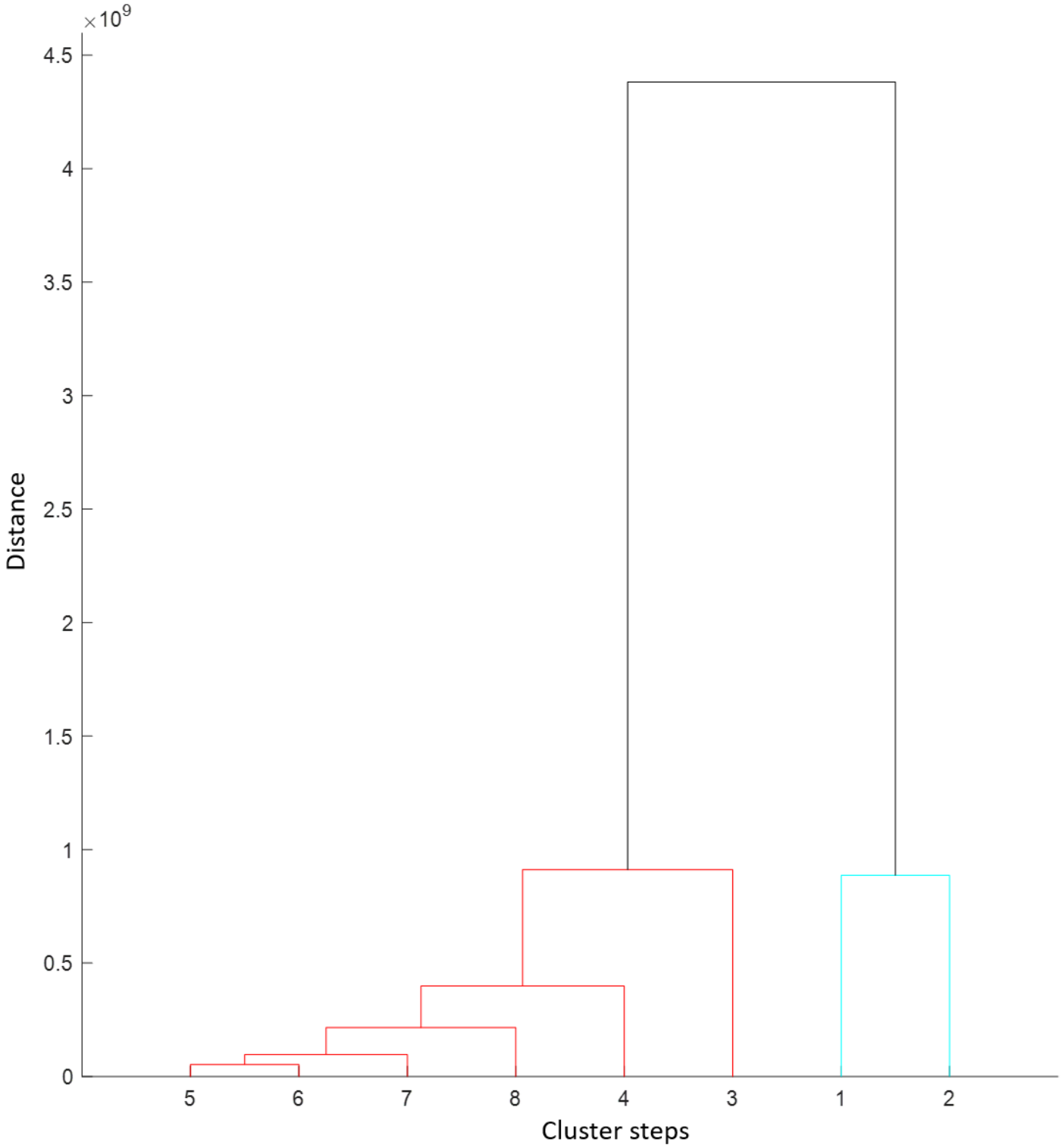


Figure 3

Hierarchical Clustering: Optimized Dendrogram

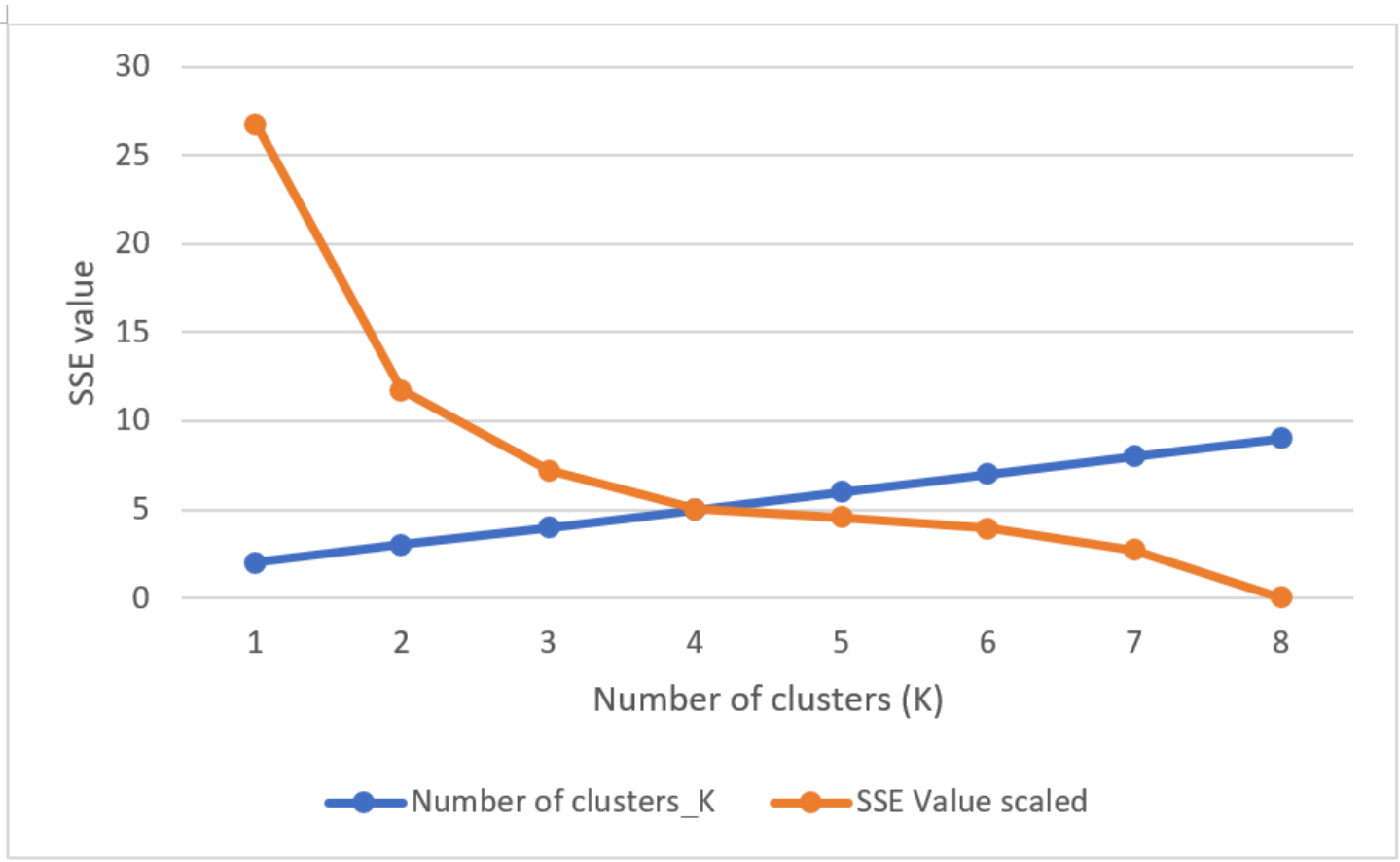


Figure 4

Elbow Criterion for Cluster Analysis