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Research article

Reliability-based analysis of horizontal curve design by evaluating the impact of vehicle automation on roadway departure crashes and safety performance

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A B S T R A C T

Roadway departure (RwD) crashes are significant safety concerns, especially at horizontal curves. The design of these curves plays a crucial role in mitigating RwD crashes. Thus, a thorough understanding of the interaction between driver behavior, vehicle automation, and geometric design is vital. Substantive safety, which emphasizes the inherent safety in a road's design and function, serves as the foundation of our approach. Building on this, the study employs a safe system approach to investigate the performance of horizontal curves under both non-automated and partially automated conditions, using a reliability-based analysis focusing on Stopping Sight Distance as the primary driver demand. Factors including Perception-Brake Time and Take-Over Time for automated vehicles are examined. The analysis covers horizontal curves, characterized by their geometric design and crash data. Our findings highlight a shift in the performance of horizontal curves under automation, emphasizing the need to consider automation in roadway design within the safe system approach. This study demonstrates how a reliability-based analysis can guide designers in making informed decisions regarding the geometric design of horizontal curves to reduce RwD crashes. To enhance transportation safety in the era of increasing automation, ongoing exploration of the relationships between driver behavior, automation, and road design is indispensable.

1. Introduction

The "Guide for Reducing Collisions on Horizontal Curves" (NCHRP Report 500, Volume 7) highlights that about 25 % of annual road fatalities in the United States happen due to vehicle crashes on horizontal curves, predominantly in rural areas on two-lane secondary highways. Notably, 76 % of these fatal crashes involve a single vehicle colliding with fixed objects or overturning, termed as Roadway Departure (RwD) crashes [1]. These crashes often result from factors such as excessive speed, driver distraction, impairment, or inadequate curve design and signage [2]. The Safe System Approach is a universally endorsed safety blueprint for road transit network design and governance, emphasizing designing roadways that are tolerant of human error and accommodate diverse road users [3].

Traditional horizontal curve design methodologies focus on nominal safety, adhering to deterministic design criteria. However, the need for substantive safety, emphasizing actual safety performance within design uncertainties, is gaining recognition [4], which leads

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to identifying system vulnerability as a significant hidden variable that can greatly impact the reliability and safety performance of horizontal curves [5].

Limit State Design (LSD) is a method that assesses the safety and reliability of systems like horizontal curves under varied demands and uncertainties [6], such approach helps in identifying potential safety hazards and developing robust design solutions accounting for real-world driving conditions' dynamic and uncertain nature.

The unpredictable nature of human drivers and their varying characteristics necessitate a nuanced understanding of human factors in roadway design [7]. Advanced Driver Assistance Systems (ADAS) can improve road safety but also present hazards, as overreliance may lead to risk homeostasis, where drivers grow complacent due to system usage [8–10]. The evolving landscape with increasing vehicle automation necessitates considering the challenges and opportunities related to emerging technologies in roadway infrastructure design [11].

This paper introduces a comprehensive understanding of horizontal curve design reliability, addressing uncertainties in driver behavior and vehicle automation to reduce Roadway Departure (RwD) crashes. It proposes a framework integrating various analysis techniques to develop Limit State Functions (LSFs) for evaluating curve performance under different conditions. The study advocates for a holistic roadway design approach, incorporating both traditional aspects and new challenges posed by vehicle automation.

The aim is to guide future transportation safety and engineering work towards robust design methodologies. As vehicle automation progresses, it's essential to address the safety and design implications of this technological shift. The study empirically highlights the need to design for both human drivers and automated vehicles, calling for ongoing research and collaboration among professionals, policymakers, and industry stakeholders to safely integrate new technologies into transportation systems.

We assume that automated vehicles and drivers adhere to the posted speed limits, aligning with the premise that automation is designed to comply with traffic regulations meticulously. This assumption allows us to isolate and study other variables like Take-Over Time (TOT) and geometric design in detail, laying down the groundwork for future studies where speed variations and compliance will be explored more extensively. By blending rigorous analysis with practical insights, this study contributes to the efforts to improve transportation infrastructure safety and reduce RwD crashes, fostering a safer and more efficient transportation future.

2. Background

In a concerted effort to secure the lives of road users, reducing RwD crashes remains a focus for both transportation agencies and research communities. Multiple strategies, encompassing holistic advancements in infrastructure, nuanced driver education initiatives, and innovative traffic management techniques, have been deliberated and executed. The exploration and perfection of vehicle automation technologies are undertaken in collaboration with industry stakeholders. This paper seeks to further distill the complexities of horizontal curve design reliability, building on a plethora of prior studies, and aims to illuminate the intricate interplay between various impactful factors on horizontal curve safety.

2.1. Infrastructure improvements and driver education

The need for enhanced safety has steered focus toward groundbreaking infrastructure improvements, including the implementation of robust barriers, advanced delineation of roadway boundaries, and heightened visibility through improved pavement markings [12]. Such modifications, together with the expansion of shoulder widths and the enhancement of curve signage, are pivotal in both the prevention and mitigation of RwD crashes. Moreover, cultivating safe driving habits and reinforcing adherence to traffic regulations are achieved through comprehensive driver education and stringent enforcement, creating an environment conducive to roadway safety [13].

2.2. Traffic management strategies

Implementing intelligent transportation systems, including advanced traffic signal systems, propels the safety and efficiency of traffic flow, mitigating potential incidents that may culminate in RwD crashes [13]. By furnishing real-time, actionable information to drivers, these systems facilitate informed decision-making and timely responses to evolving traffic scenarios. Proactive strategies such as adaptive speed limits and early incident detection serve as additional layers of protection, mitigating potential hazards and refining the overall safety landscape.

2.3. Challenges in vehicle automation

The progressive evolution of ADAS indicates the initiation of fully automated vehicles, introducing novel challenges and intricacies in roadway safety. The diverse proficiencies and experiences of drivers, coupled with varying automation levels, necessitate a comprehensive understanding and meticulous addressing of the limitations inherent to automation systems [14]. Recognizing and addressing the nuanced challenges are paramount to seamlessly integrating these groundbreaking technologies into our prevailing transportation frameworks, vehicles on the road today have varying Levels of Automation (LoA) (0–3) that require the full attention of the human operator due to their limitations [15]. As the transportation landscape continues to evolve and automated vehicles become more prevalent, it will be important to account for the unique challenges and opportunities associated with these emerging technologies in the design of horizontal curves and other roadway infrastructure [16].

The path and trajectory of vehicles on highways and streets depend on the diverse abilities, training, and experience of drivers, as well as the sight distance available to them. The driver's perception is challenged by competing sources of information on the roadway that is expected and sometimes unexpected [17], or communication demands from the world outside the vehicle [18].

For human drivers, perception-brake time (t) is the time required to perceive a hazard and initiate braking [19]. However, distracted driving, fatigue, and other factors can result in significant lane position and perception-brake time deviations, affecting the available sight distance and overall safety performance of the horizontal curve [20,21].

In the context of vehicle automation, drivers are expected to be engaged with the driving task, as the vehicle may issue a take-over request (TOR). The time it takes the driver to perceive the request and take over the task is known as the take-over time (TOT) [15]. Several factors affect TOT, such as the urgency of the situation, engaging in non-driving tasks, and the type of TOR [22,23]. It is also important to note that the TOT does not replace the perception-brake time; rather, it is an addition to it [24]. Fig. 1 displays a non-scale drawing of a possible scenario of a TOR issued slightly prior to a curve. Additionally, the effectiveness of lane-keep and lane-centering assist systems varies depending on road alignments [25]. Although the reliability of vehicle autonomy is not within the scope of this study, these uncertainties are related to the safety design of horizontal curves which is generally connected to RwD crashes. It is crucial to address these challenges and understand the limitations of vehicle automation systems to ensure their safe integration into the existing transportation infrastructure.

2.4. Reliability analysis in roadway design

Applying Limit State Design (LSD) and categorizing Limit State Functions (LSFs) afford a detailed examination of structural performance under varied conditions [26,27]. A variety of research has examined the probabilistic analysis of roadway design uncertainties, examining various aspects such as safety levels, vehicle parameters, and sight distance constraints. This section presents a review of the key studies in this field, highlighting their contributions to reliability analysis in roadway design. Jalayer and Zhou [28] proposed the use of reliability indices to gauge safety levels on rural two-lane roads. Their study emphasized the importance of accounting for uncertainties in geometric design parameters and offered a novel approach to evaluate the safety of road segments using reliability indices. Ghasemi et al. [19] conducted research that focused on evaluating space headway using probabilistic analysis. Their primary objective was to determine the appropriate space headway that would ensure safe driving conditions on rural two-lane roads. They utilized probability theory to identify the optimal space headway values based on traffic flow characteristics, which could then be used for roadway design purposes. You et al. [29] investigated the effects of vehicle parameters and superelevation on vehicle skidding and rollover in horizontal curve design. Their study provided valuable insights into the interactions between vehicle dynamics and road geometry, highlighting the significance of considering vehicle parameters in roadway design to ensure safety. Essa et al. [30] carried out a multi-mode reliability analysis for horizontal curve design, which integrated both deterministic and probabilistic approaches. Their research demonstrated the feasibility of applying reliability analysis to address uncertainties in horizontal curve design and provided a comprehensive framework for evaluating the safety performance of distinctive design scenarios. De Santos-Berbe et al. [31] focused on 2D and 3D sight distance estimation methods for horizontal curves on rural highways. They compared the accuracy and reliability of various estimation methods and provided recommendations for selecting the most appropriate method in different roadway design situations. In their study, Andrade-Cataño et al. [32] applied a probabilistic approach to evaluate the risk level associated with sag curve designs and assessed the effect of variables involved in headlight sight distance (HSD) on the probability of noncompliance. The results showed that variables modelling headlight features significantly affect the risk level and that the risk

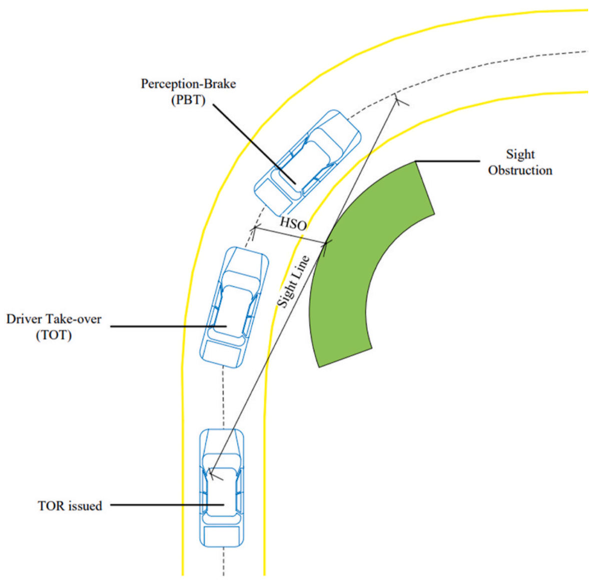

Fig. 1. Possible TOR scenario on a curve.

associated with design outputs considered equivalent by the standard varies significantly. Recent studies have developed reliability-based frameworks for addressing risk associated with sight distance limitations. Shalkamy and El-Basyouny [33] devised a framework for evaluating the risk associated with sight distance limitations in horizontal curve design, while Gargoum et al. [34] assessed compliance with sight distance requirements on a network level. In another study, Shalkamy et al. [35] used Structural Equation Modelling (SEM) to investigate the indirect influence of horizontal curve attributes on safety. They found that curve features like deflection angle and chord length significantly impacted the probability of non-compliance, which in turn affected collision frequency. This emphasized the need to consider multiple curve attributes in the design of horizontal curves rather than solely focusing on curve radius. Goyani et al. [36] calculated reliability indices for 3D highway alignments in mountainous terrain, offering insights into the challenges associated with complex roadway design in such environments. Dhahir and Hassan [37,38] proposed a probabilistic, safety-focused approach to designing horizontal curves on two-lane rural highways. They developed safety performance functions to relate reliability indices to expected safety performance, thus providing a direct link between reliability analysis and roadway safety.

Table 1 below provides a succinct overview of the seminal works in reliability analysis.

While these studies have provided invaluable insights, there is a need for more comprehensive research. Therefore, we incorporate the impact of Take-Over Time (TOT) and lane deviation on the Horizontal Sightline Offset (HSO) in the context of evolving driver behavior and growing vehicle automation technologies, ensuring a rounded understanding of roadway safety amidst the advent of vehicle technologies.

Our study takes a comprehensive approach by integrating driver behavior, vehicle automation, and geometric design into the SLSFs and reliability analysis. This integration aims to provide a holistic view, enabling transportation engineers and designers to comprehend the interplay between these factors. Such an understanding is pivotal for designing and implementing horizontal curves that promise enhanced safety and efficiency for every road user.

3. Data collection framework

The process of analyzing the selected horizontal curves requires accurate information on site characteristics and crash occurrences, facilitating a thorough investigation of the factors affecting roadway safety. This comprehensive information allows us to identify potential hazards and develop targeted interventions to enhance the safety of horizontal curves in the context of driver behavior and vehicle automation. In this section, we discuss the framework and techniques applied to select and gather data on horizontal curves.

3.1. Site selection and crash data

To analyze selected horizontal curves, we needed detailed site characteristics and crash data, enabling us to scrutinize the factors influencing roadway safety deeply. We chose curves using an approach mirrored from Donnell et al. [39] and utilized crash data from New Jersey between 2017 and 2020. We defined curve-related crashes as those occurring within 150 ft upstream of the point of curvature (PC) or point of tangency (PT), following the methodology of Donnell et al. [39]. We then filtered this data to represent Roadway Departure (RwD) crashes and conducted a hotspot analysis to identify areas with significantly high and low crash occurrences [40], as illustrated in Fig. 2.

The hotspot analysis tested the hypothesis that significant clusters of crashes, termed 'Hot Spots,' would be identified where RwD crashes are more frequent within 150 ft of each other. Conversely, 'Cold Spots' would be identified as areas with significantly fewer crashes, suggesting a lower risk or an adequate curve design with sufficient available sight distance. We then selected curves from both Cold Spots and Hot Spots to capture diverse safety performance and ensure a comprehensive analysis.

3.2. Geometric analysis: CAD drawing and surface profile

To thoroughly evaluate the safety of the selected curves, we created precise CAD drawings from high-resolution aerial LiDAR data

Table 1
Reliability analysis Literature in roadway safety and design.

Author(s)	Focus Area	Key Contributions	Year
Jalayer and Zhou [28]	Safety levels on rural two-lane roads	Introduced reliability indices for safety evaluation	2016
Ghasemi et al. [19]	Evaluation of space headway	Utilized probabilistic analysis for optimal headway values	2016
You et al. [29]	Vehicle parameters and road geometry interactions	Explored vehicle dynamics and roadway design interplay	2012
Essa et al. [30]	Multi-mode reliability analysis for horizontal curve design	Integrated deterministic and probabilistic approaches	2016
Shalkamy and El-Basyouny [33]	Risk evaluation related to sight distance limitations	Developed a framework for horizontal curve design	2020
Gargoum et al. [34]	Compliance with sight distance requirements	Assessed sight distance requirements at the network level	2022
Shalkamy et al. [35]	Influence of horizontal curve attributes on safety	Employed SEM to investigate curve attributes	2021
Goyani et al. [36]	Reliability indices for 3D highway alignments	Addressed challenges in designing roads in mountainous terrain	2022
Dhahir and Hassan [37,38]	Probabilistic, safety-focused approach to design	Linked reliability analysis to expected safety performance	2019

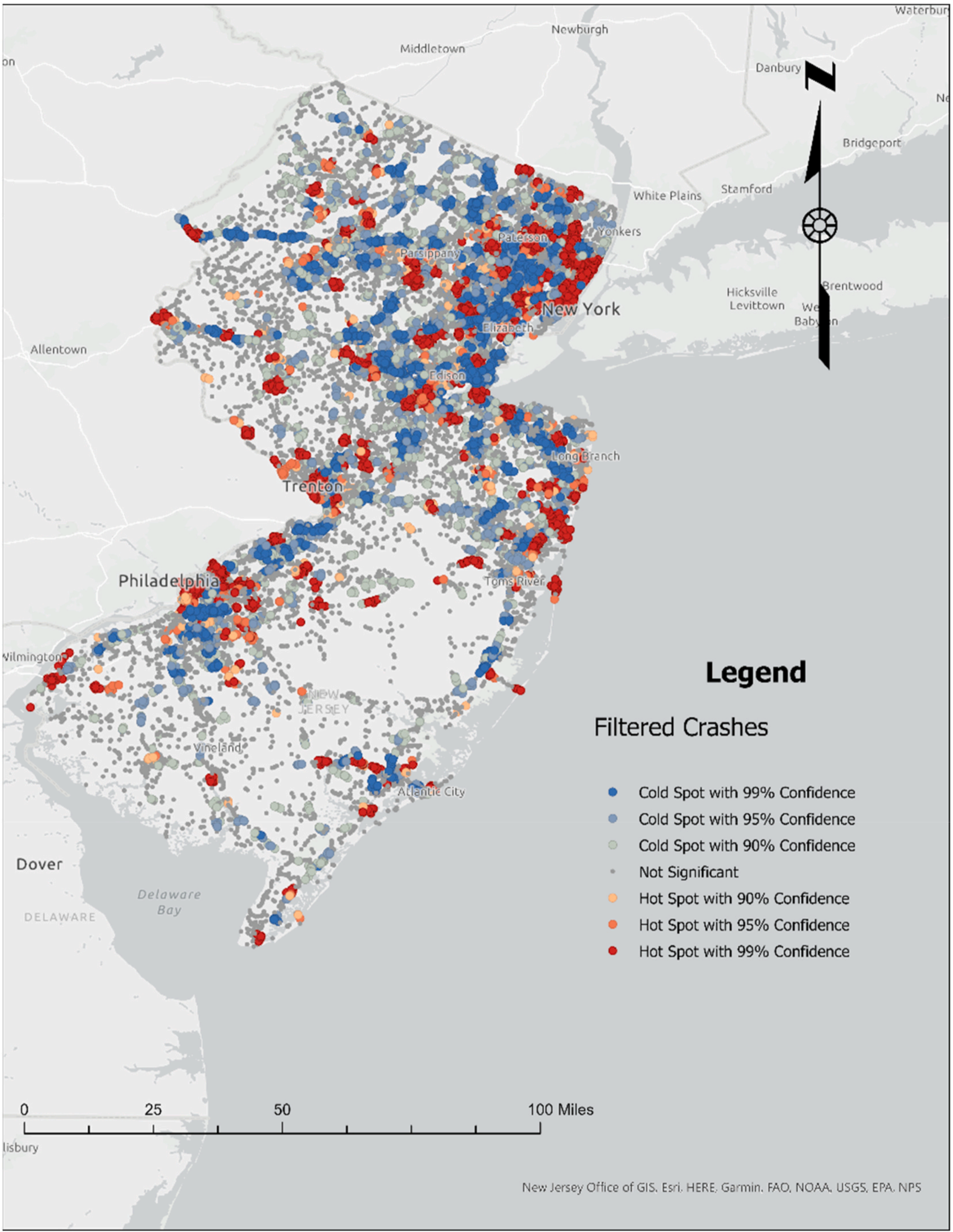

Fig. 2. Hotspot visualization of filtered crash data.

and extracted the roadway's surface profile for further analysis of the grade. We delineated the horizontal alignment on the extracted surface, plotting key curve components like the curve radius, point of curvature (PC), and point of tangency (PT) to construct a detailed depiction of the roadway's geometric design. Fig. 3 displays a horizontal alignment's CAD drawings.

Table 2 displays an example report of an alignment profile, which includes information about the station, easting, northing, elevation, bearing, alignment radius, entity type, and gradient. This data is essential for understanding the geometric design and the analysis of sight distances for the selected horizontal curves.

The integration of crash data, CAD drawings, and surface profiles permits a comprehensive examination of the factors impacting the safety performance of horizontal curves. This holistic approach allows for the identification of potential hazards and enables the

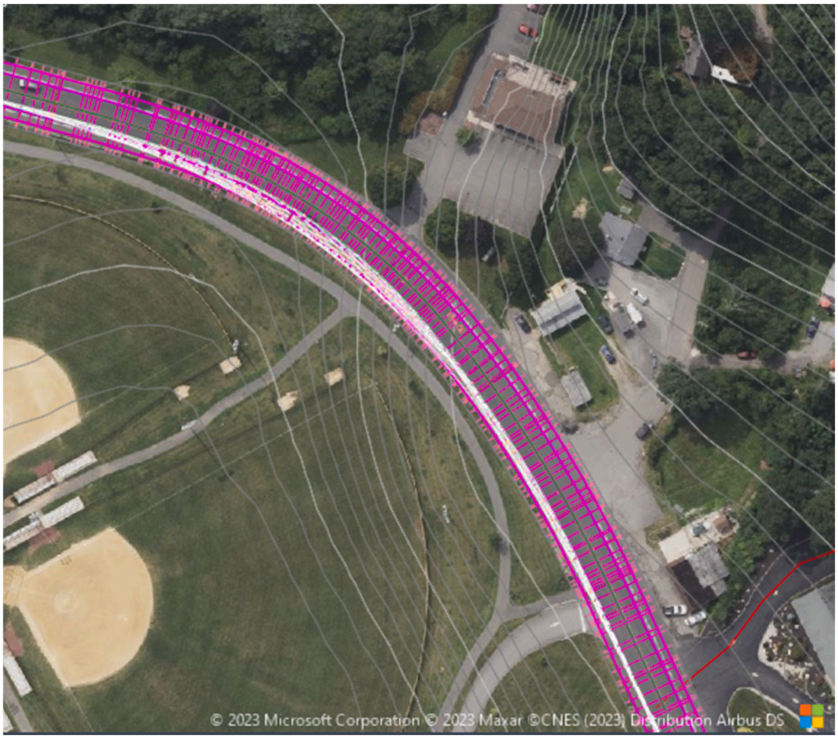

Fig. 3. Horizontal Alignment CAD drawing with contours from LiDAR data.

Table 2
Report of an alignment profile.

Station (ft)	Easting (ft)	Northing (ft)	Elevation (ft)	Bearing	Alignment Radius (ft)	Entity Type	Gradient (ft/ft)
1 + 35.00	362199	684892	361.54	162° 12′ 10.70″	1600	Curve	−12.00 %
1 + 40.00	362201	684887	361.52	162° 1′ 6.15″	1600	Curve	−12.00 %
1 + 45.00	362202	684882	361.51	161° 50′ 1.59″	1600	Curve	−12.00 %
1 + 50.00	362204	684877	361.48	161° 38′ 57.05″	1600	Curve	−12.00 %
1 + 55.00	362205	684873	361.44	161° 27′ 52.49″	1600	Curve	−12.00 %
1 + 60.00	362207	684868	361.4	161° 16′ 47.94″	1600	Curve	−12.00 %
1 + 65.00	362209	684863	361.36	161° 5′ 43.39″	1600	Curve	−12.00 %
1 + 70.00	362210	684858	361.33	160° 54′ 38.83″	1600	Curve	−12.00 %
1 + 75.00	362212	684854	361.29	160° 43′ 34.28″	1600	Curve	−12.00 %
1 + 80.00	362214	684849	361.25	160° 32′ 29.724″	1600	Curve	−12.00 %
1 + 85.00	362215	684844	361.21	160° 21′ 25.17″	1600	Curve	−12.00 %
1 + 90.00	362217	684840	361.17	160° 10′ 20.62″	1600	Curve	−12.00 %
1 + 95.00	362219	684835	361.13	159° 59′ 16.06″	1600	Curve	−12.00 %
2 + 00.00	362220	684830	361.09	159° 48′ 11.51″	1600	Curve	−12.00 %

development of targeted interventions to enhance curve safety considering driver behavior and vehicle automation. The resulting insights form the basis for informed safety improvements and innovative enhancements in the design of horizontal curves.

4. Methods

In this section, we outline the methodology applied to scrutinize the impact of driver behavior and vehicle automation on the safety design of horizontal curves. We formulate a comprehensive limit state function, evaluating the safety of these curves by considering factors such as lane deviation, perception-braking time (t), takeover time (TOT), deceleration rate (a), and the grade (G) of the pavement.

4.1. Capacity of the geometric design

Evaluating the geometric design capacity of a horizontal curve is critical to ensuring unobstructed sightlines and sufficient distance for drivers to perceive, process, and respond to potential hazards. We calculate the available sight distance (ASD) using equation (1):

$$ASD = \left(\frac{R}{28.65}\right)\left(\cos^{-1}\left(1 - \frac{HSO}{R}\right)\right) \quad (1)$$

Here, R denotes the curve's radius, and HSO represents the horizontal sightline offset. We consider the standard deviation of the lane position (SDLP) from Iio et al. [41] as a measure of human error and uncertainties associated with vehicle lane centering assist technologies.

4.2. Demand by the driver/operator

Assessing the safety of horizontal curves necessitates a comprehensive understanding of the numerous factors impacting a driver or operator's performance. One primary consideration is the Stopping Sight Distance (SSD), the minimum distance required for a vehicle to come to a complete stop. The SSD accounts for the driver's perception and braking time, which are influenced by factors such as neurological capacity, mental workload, and driving experience [42]. The road surface design also plays a role in these factors, collectively impacting a driver's ability to perceive, process, and respond to changing road conditions or traffic situations promptly. The calculation of SSD is contingent upon several critical factors, including Speed (V), Deceleration Rate (a), Grade (G), and Perception-Brake Time (t) [17], as shown in equation (2):

$$SSD = 1.47tV + \frac{V^2}{30 \times \left(\frac{a}{32.2} + G\right)} + L_{front-eye} \quad (2)$$

For automated vehicles, the Takeover Time (TOT) must also be considered. TOT represents the time required for the driver to regain control of the vehicle after receiving a takeover request (TOR) from the automated system (Zhang et al., 2019). The modified equation for stopping sight distance, which takes vehicle automation into account, is represented in equation (3):

$$SSD_{Auto} = 1.47(t + TOT)V + \frac{V^2}{30 \times \left(\frac{a}{32.2} + G\right)} + L_{front-eye} \quad (3)$$

The parameter $L_{front-eye}$ represents the distance from the front of the vehicle to the driver's eye. Introduced by Wood and Donnell (2017), this parameter has been employed in subsequent studies by Shalkamy and El-Basyouny (2020) for the reliability analysis of horizontal curves.

The mean and standard deviations of the model parameters are presented in Table 3, along with their respective sources.

For perception and braking time from Wood & Zhang [21], the mean and standard deviation were obtained from 2971 crash/near crash events focusing solely on braking, to accurately reflect diverse driver responses to emergencies and hazards.

The average Take-Over Time (TOT) from Zhang et al. [23] was determined from a meta-analysis of studies published primarily after 2015, with data spanning from 2000 to 2018. This analysis consolidated observations from multiple studies, encompassing a variety of conditions and contexts to provide a comprehensive understanding of TOT in different scenarios.

The SDLP value from Iio et al. [41] indicates the variability of a vehicle's lateral position on the road, reflecting the driver's ability to maintain a consistent lane position while navigating the curve, which affects the equivalent HSO.

In the study by Wood & Donnell [43] $L_{front-eye}$, distance was estimated from 100 vehicles - 57 passenger cars, 20 pickups, 13 SUVs, and 10 minivans - by measuring from each vehicle's front to the driver's headrest, assuming drivers align their heads with the headrest. This method provided a standardized way to approximate driver's eye position across different vehicle types.

4.3. Limit state function and reliability analysis

To accurately assess the safety performance of a road or system and to account for uncertainties in driver behavior, vehicle automation, and environmental conditions, it's imperative to formulate Limit State Functions (LSFs). LSFs act as instrumental tools in evaluating the safety margin of a horizontal curve, allowing transportation engineers to refine and enhance the design of horizontal curves.

In this study, represented in equation (4), we define the LSF (g) as the difference between the Available Sight Distance (ASD) and the required Stopping Sight Distance (SSD):

$$g = R - Q \quad (4)$$

Table 3
Mean and standard deviations of model parameters.

Parameter	Mean	SD	Source
t (s)	1.66	1.36	[21]
TOT (s)	2.72	1.45	[23]
a (ft/s^2)	13.78	1.97	[44]
$SDLP$ (ft)	0.24	0.10	[41]
HSO (ft)	Measured HSO	SDLP	This study
$L_{front-eye}$ (ft)	7.74	0.42	[43]

Here, R represents the resistance—interpreted as the ASD, and Q signifies the demand—equivalent to the required SSD. A positive LSF value indicates a safe curve, while a negative one denotes potential non-compliance or an unsafe condition.

Fig. 4(a) provides a sample distribution of ASD and SSD stemming from equations (1) and (2). In contrast, Fig. 4(c) portrays the distributions sourced from equations (1) and (3). Fig. 4(b) and (d) present the safety margin distribution from the limit state function (equation (4)).

4.3.1. Types of LSFs

LSFs can be broadly segmented into two types: Service Limit State Functions (SLSFs) and Ultimate Limit State Functions (ULSFs), each designed for specific applications. In the context of this study, due to the premise of adhering to speed, our chosen LSF falls under the SLSF category. The distinctions and applications of these LSF types are encapsulated in Table 4.

4.3.2. Addressing uncertainties with Monte Carlo simulations

To resolve uncertainties in ASD and SSD values, we utilize Monte Carlo simulations, generating multiple random samples for each variable and statistically analyzing the outcomes. The probability of non-compliance (P_{nc}) is calculated in equation (5):

$$P_{nc} = \frac{\sum_{i=1}^{n} I(\boldsymbol{g}_i < 0)}{n} \tag{5}$$

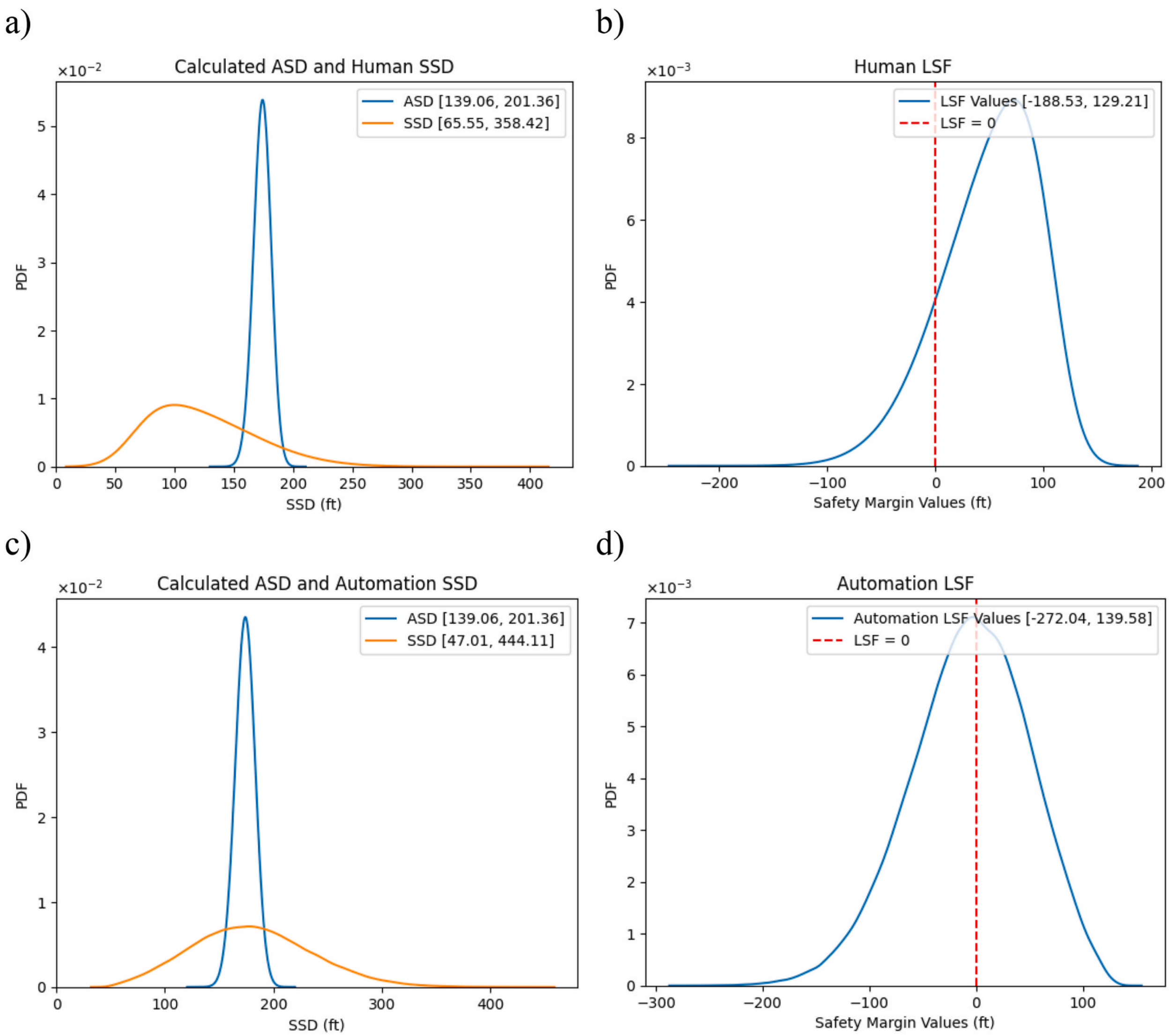

Fig. 4. Example distribution of ASD, SSD (a)(c), and LSF for non-automated (b) and automated (d) scenarios.

Table 4
LSF types and applications.

Type of LSF	Application	Description
Service Limit State	Regular Operational Performance	Covers areas like driver's line of sight, vehicular stability.
Ultimate Limit State	Extreme Conditions	Evaluates the ability of horizontal curves to withstand extreme conditions, such as severe weather, heavy loads, or high-speed impacts.

4.3.3. Reliability analysis and assessment of vulnerability

This study employs reliability analysis to estimate the probability of failure for each curve, considering variations in driver behavior, geometric design parameters, and environmental factors. We determine the reliability index (β) using the inverse cumulative distribution function of the standard normal distribution, shown in equation (6):

$$\beta = -\Phi^{-1}(P_{nc}) \tag{6}$$

Several conventional approaches for computing the reliability index exist, including the First- Monte Carlo simulations were selected for their reliability in estimating P_{nc} and β, allowing for the consideration of the effects of uncertainties in ASD and SSD on the safety evaluation of horizontal curves. The vulnerability associated with the reliability index denotes the likelihood of a system experiencing failure, given specific uncertainties and conditions.

5. Results and discussion

Table 5 details the analysis results from seven distinct horizontal curves (C-1 to C-7), considering both No Automation and Automation conditions. It encompasses several parameters including posted speed limit (PSL), grade at the point of curvature (PC), curve radius, the ASD range, Horizontal Sightline Offset (HSO), the number of crashes observed between 2017 and 2020, and the values for P_{nc} and β for both conditions.

A closer examination of the relationship between β and the number of crashes reveals a logarithmic pattern for both scenarios. For the No Automation scenario, the logarithmic fit yields equation (7), with a high determination coefficient of $R^2 = 0.926$, as depicted in Fig. 5:

$$\beta = -0.464\, log(x) + 1.128 \tag{7}$$

Similarly, in the Automation scenario, the relationship follows equation (8):

$$\beta = -0.388\, log(x) - 0.670 \tag{8}$$

An R^2 value of 0.839 was determined, as shown in Fig. 6. This also represents a strong negative correlation, albeit slightly weaker than in the non-Automation scenario.

We implemented a reliability-based analysis to evaluate the performance of horizontal curve design accounting for uncertainties associated with driver behavior and vehicle automation. The logarithmic relationship between β and the number of crashes reveals a strong negative correlation in both scenarios, implying that as the number of crashes increases, the reliability index decreases logarithmically. These logarithmic relationships emphasize the crucial role of geometric design improvements in reducing the number of crashes and enhancing the reliability of horizontal curves.

The emphasis on Take-Over Time (TOT) and its addition to the response time (t) in evaluating the SSD provides insights into valid scenarios in partial automation, the lower β values in Automation scenarios compared to No Automation scenarios illustrates the change in the performance of horizontal curves under partial automation conditions, highlighting the importance of considering automation in designing and assessing horizontal curves.

Table 5
Reliability analysis results.

Curve	PSL (mph)	Grade at PC	ASD Min-Max (ft)	Radius (ft)	HSO (ft)	No. of Crashes	No Automation		Automation	
							P_{nc}	β	P_{nc}	β
C-1	25	7 %	79.77–104.71	135	8	20	0.658	−0.406	0.978	−2.022
C-2	25	12 %	88.48–148.59	360	5	6	0.402	0.248	0.925	−1.436
C-3	35	10 %	102.15–160.24	450	5	53	0.731	−0.616	0.986	−2.213
C-4	35	−2 %	124.40–216.23	950	4	18	0.635	−0.345	0.973	−1.932
C-5	40	−10 %	210.04–284.39	1120	9	10	0.459	0.103	0.93	−1.475
C-6	45	0 %	285.69–351.71	1275	10	6	0.332	0.433	0.893	−1.243
C-7	55	−15 %	434.33–486.36	1400	19	35	0.682	−0.475	0.968	−1.852

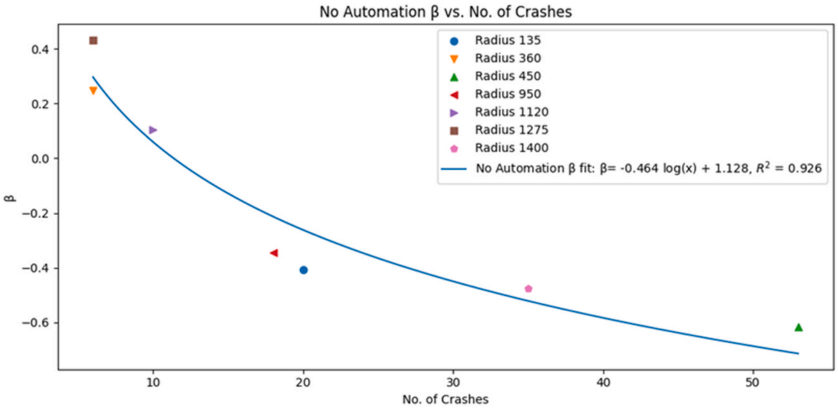

Fig. 5. Logarithmic fit of β vs No. of Crashes for Non-Automation Scenarios.

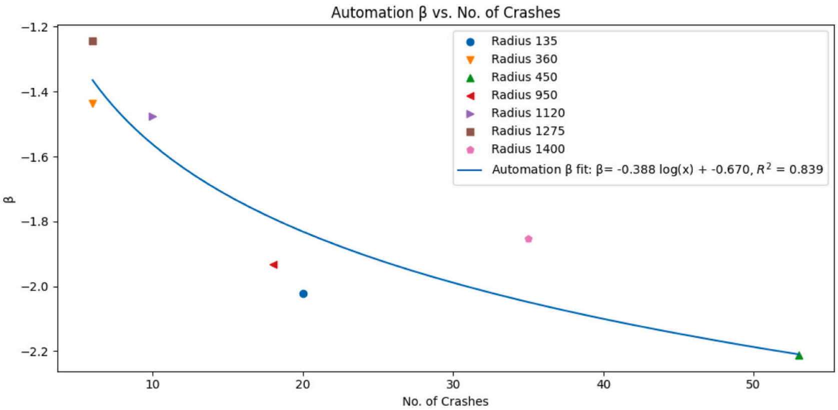

Fig. 6. Logarithmic fit of β vs No. of Crashes for Automation Scenarios.

6. Limitations and practical implementations

While this study provides valuable insights into the safety and reliability of horizontal curve design, its application in real-world scenarios encounters certain limitations. To draw more comprehensive conclusions about the reliability of horizontal curves under automation, future studies should incorporate a broader range of automation aspects, exploring their multifarious impacts on safety conditions. The study also did not account for factors like interactions with pedestrians, cyclists, environmental conditions, lighting, and road surface quality, all of which can significantly influence the safety performance of horizontal curves.

Additionally, the data used in this study is region and time-specific, potentially limiting the broader applicability of the findings. Further research is needed to validate the study's methodology across different geographical locations and conditions and to consider the evolving landscape of vehicle technology and roadway infrastructure.

Despite these limitations, the study's outcomes offer practical utility. They highlight the importance of considering driver behavior, vehicle automation, and geometric design in enhancing the safety of horizontal curves. This information is crucial for transportation engineers and policymakers in developing effective strategies to improve roadway safety, particularly in reducing Roadway Departure (RwD) crashes.

7. Conclusion

This study sheds light on road safety challenges present in horizontal curves, particularly with the high incidence of Roadway Departure (RwD) crashes. These crashes often involve factors like distractions, impairment, and poor curve design that does not meet the demand of all road users. Addressing the interplay of human behavior, vehicle automation, and road infrastructure is therefore critical.

The research underscores the need to shift from traditional nominal safety in curve design to a more comprehensive substantive safety approach. Emphasizing the Safe System Approach, which aims for roads that forgive human errors and accommodate diverse users and vehicles, is increasingly vital. Our research investigates the reliability of horizontal curve design, exploring the dynamics between driver behavior, vehicle automation, and curve geometry. However, the study acknowledges its limitations in fully capturing the range of potential conditions and scenarios.

Central to our investigation is the blend of horizontal curve design considerations with human driving patterns and the rise of vehicle automation. This aspect calls for further research in the rapidly changing field of vehicle automation. By integrating reliability-based analysis, road designers can significantly improve safety, particularly in the context of automated vehicles. Our findings highlight the intricate connections between curve design, driver behavior, and automation, emphasizing the ongoing need for research to enhance road safety in an era of advancing automation.

As we transition into a new era of transportation, seamlessly integrating human-driven and automated systems into road design is essential. Embracing the substantive safety model and advocating for the Safe System Approach are fundamental to the future of transportation. With proactive research and innovation, we aim to create safer, more efficient roadways that meet the demands of all road users.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon request.

CRediT authorship contribution statement

Omar Al-Sheikh: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Seyed Hooman Ghasemi:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization. **Mohammad Jalayer:** Writing – review & editing, Validation, Supervision, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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