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Predictable motorway ramp curves are safer

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ABSTRACT

Motorway safety depends largely on curve geometry and driver behaviour, a relationship that has implications for research and practice. This paper introduces a novel approach to quantifying geometric design consistency, defined as the degree to which drivers' expectations of curve radii match actual road geometries. The hypothesis is that if a driver expects a larger curve than that actually present, an accident might occur because of an excessively high approach speed. To test this hypothesis, this study uses Dutch motorway data, including ramp and curve characteristics, as well as crash frequencies. The data were employed in three steps: 1) constructing a Bayesian model that mimics drivers' expectations, 2) testing the predictions of this model against real curve characteristics, and 3) examining the relationship between disparities in expectations, reality, and crash frequency. The results indicated a positive correlation between disparities in expectations, reality, and crash frequency. This finding suggests that the crash frequency is higher when drivers expect a larger curve than what is present. The Tree Augmented Naïve Bayesian Network (TAN) reveals the complexity of curve expectations, demonstrating that drivers anticipate larger radii in connector ramps and higher speeds with gentler curve angles. Applying this research to motorway design involves using TAN predictions and crash frequency models to assess safety in motorway curve design, which could proactively improve road safety.

1. Introduction

Motorway ramp curves pose a significant challenge to driver safety. (Davidse and Duijvenvoorde, 2024), with numerous factors influencing their level of risk (Ryan et al., 2022; Shalkamy et al., 2021). Safe driving behaviour on curves is heavily dependent on the radius of the curve itself, with larger radii generally leading to safer driving conditions, because less speed reduction is needed (Rondora et al., 2022). Moreover, inadequate coordination between geometric elements of horizontal curves, particularly the radius, can result in unsafe driving speeds, further increasing the risk of accidents (Sil et al., 2020). In addition to the curve radius, factors such as the pre-deceleration speed, type of roadway, sight distances, and cross-section characteristics all contribute to determining the point at which deceleration begins upon entering a curve (Vos et al., 2021).

Traditional studies on geometric design consistency – e.g. Lamm et al. (1999) – provide guidelines on speed differences in consecutive design elements to provide comfortable driving. This is still a behavioural approach to driving behaviour, focusing on the correlation between speed and design (Michon, 1985). In contrast, the cognitive approach takes a broader perspective and a more comprehensive approach by considering how the visual input is translated into observable output by the driver. For most environments, it remains unknown which mental templates, which are built on experience, are used by drivers (Salmon et al., 2014). Accumulated driving experience can aid drivers in appropriately adjusting their speed when approaching curves (Elvik, 2022). However, it remains unclear whether drivers' expectations regarding the need to adjust their speed align with the actual safety characteristics of curves. This raises the main research question of this paper:

Does a mismatch in drivers' expectations of motorway ramp curves align with the safety implications?

Understanding how drivers perceive and anticipate road geometry is essential for translating knowledge of driver behaviour into safer road design. This study specifically hypothesises that a mismatch between drivers' perceived and actual curve radii may increase crash risk. To investigate this, quantification of driver expectations is needed, despite the challenge that these expectations cannot be directly measured (Walker et al., 2011). However, research shows that people develop expectations based on real-world statistical patterns (Griffiths and Tenenbaum, 2006; Seriès and Seitz, 2013) and that drivers apply similar learning mechanisms in spatial navigation (Chanales et al., 2017; Graves et al., 2022).

Building on this, it is assumed that drivers infer safe speeds by

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statistically learning regularities in the road environment (Theeuwes, 2021). This form of statistical learning is best described in Bayesian terms of probability (Tenenbaum et al., 2011). Accordingly, a Bayesian model is developed in this research to represent drivers' expectations of curve geometry and compare its predictions with actual curve characteristics. By analysing the relationship between discrepancies in expected and actual radii and crash frequency, this study provides new insights into how driver expectations can be integrated into safer road design practices.

This paper starts in section 2 with a description of the research context and the foundations to position the steps described above. Next, section 3 discusses the dataset and methods used in this research. Section 4 presents the results of this study, and section 5 discusses these results. Section 6 provides the main conclusions of this research.

2. Research context and foundation

This section provides the theoretical and contextual background required to understand the research presented in this paper. It positions the key concepts and methods outlined in the introduction within the existing body of knowledge and highlights relevant studies to support the steps taken in this research. Although not a comprehensive review of all related literature, this overview provides the reader with the foundational insights to evaluate the study's approach and findings independently. Therefore, it begins by describing why this study is important for providing safe road systems. Next, it covers the knowledge of design consistency. Next, it covers the driver expectations and how to model them. Finally, attention is given to crash frequency analysis because this is considered key knowledge in applying human factor knowledge in road design processes by identifying critical risk factors and revealing the complex relationships between these factors and crashes (Imprialou et al., 2016).

2.1. Proactive road design practices

Changing the built environment in the way we design safe road systems has a large impact on public health (Ederer et al., 2023). To establish a safe road system, it is important to integrate road safety knowledge into the design process and pre-empt potential accidents (Wegman, 2017). Central to this endeavour is the incorporation of human factors knowledge, which not only informs geometric design consistency models but also facilitates enhanced evaluations of road safety and the development of intelligent driver assistance systems (Pérez-Zuriaga et al., 2013). This proactive approach to road design, guided by human factors (i.e. the interaction of the driver with the road environment) knowledge, extends beyond mere considerations of geometry to encompass factors such as driver information processing, expectancy, design consistency, and error reduction (Borsos et al., 2015; Han et al., 2023; Lunenfeld and Alexander Gerson, 1984). By integrating these factors into the design process, it becomes possible to create road designs that not only accommodate the needs of drivers but also prioritise safety from the outset.

2.2. Design consistency and driver expectations

Studies suggest that design consistency, including geometric design measures and consistency indices, improves the safety of curves by reducing crashes and inconsistencies (Montella and Imbriani, 2015) and by accounting for human factors in road safety assessment. In a more conventional approach, Lamm et al. (1999) classified the consistency between successive geometric elements on rural two-lane highways as good, fair, or poor depending on the speed differential between these elements. Specifically, less than 10 km/h indicates good consistency, 10–20 km/h suggests fair consistency, and above 20 km/h signifies poor consistency. The level of consistency is furthermore influenced by the choice of speed (Luque and Castro, 2016) and distances to adjacent curves (Findley et al., 2012). A broader perspective defines geometric design consistency as the extent to which drivers' expectations align with the geometric features of the road (Malaghan et al., 2021). In this sense, motorways are the most cognitively compatible road types and are therefore the safest road type (Aarts et al., 2016). This compatibility is explained because drivers are familiar with the specific road layout of motorways and know what to expect and how to behave, which is known as a self-explaining road (Theeuwes, 2021; Walker et al., 2013).

Drivers develop these expectations based on the regularities in the road environment (Theeuwes, 2021). They anticipate steering actions based on perceived road curvature and their internal estimates of vehicle characteristics (Godthelp, 1986). However, road curvature is difficult to detect from a distance because the curve transforms into a hyperbola or kinks from a driver's perspective (Brummelaar, 1975; Riemersma, 1988). This suggests that drivers use other cues during curve approach to safely decelerate. Through repeated experiences, drivers form expectations in their memory (Ghosh and Gilboa, 2014) and associate specific road layouts with safe and comfortable speeds (Charlton and Starkey, 2017). These expectations guide drivers in selecting a safe speed during curve approach, often occurring without conscious awareness (Charlton and Starkey, 2011). It is assumed that drivers statistically infer a safe and comfortable speed given certain road elements (Griffiths and Tenenbaum, 2006; Raviv et al., 2012; Theeuwes, 2021), which is known as statistical learning (Sherman et al., 2020). This process is illustrated in Fig. 1.

In this context, drivers' expectations can be represented by probability distributions of actions to undertake – e.g. braking – given specific visual cues of the road environment, to efficiently make judgments and guide action (Frost et al., 2015; Knill and Pouget, 2004; Vos et al., 2024). This is best understood in Bayesian terms of probability (Lange & Haefner, 2022; Tenenbaum et al., 2011).

2.3. Bayesian approach to driver expectations

Drivers constantly form and update their expectations about upcoming roadway conditions by integrating past experiences with new sensory information. Recent research (Vos et al., 2024) suggests that these expectations can be effectively modelled as probabilistic beliefs within a Bayesian framework. In this view, a driver's prior experiences, stored as probability distributions in their long-term memory (Plant & Stanton, 2013), inform their initial expectations about safe speeds. For instance, on main carriageways designed for high-speed travel, drivers typically expect to encounter large curve radii that require little or no speed adaptation.

As drivers progress along the road, they continuously receive new cues, such as changes in signage, lane markings, or road geometry, which provide additional information about upcoming curves. Bayesian inference, a fundamental concept in probabilistic reasoning (Feldman, 2013), offers a formal framework for describing how these cues are integrated with prior beliefs. Specifically, Bayes' theorem combines the likelihood of observing a particular cue with the prior belief about safe speeds to compute a posterior belief that more accurately reflects the current driving environment.

Fig. 2 illustrates the dynamic process of updating beliefs. This figure extends the model presented in Fig. 1 by showing how prior beliefs about safe speeds, denoted as P(v), are continuously updated as drivers encounter new cues. In the model, a new cue, whose likelihood probabilities are stored in long-term memory, is processed in working memory, where it is combined with the existing prior. This integration results in a posterior belief about safe speed, which in turn guides the driver's behaviour.

Beyond the integration of individual cues, Bayesian belief networks also provide a powerful tool for modelling the conditional dependencies among multiple cues (Pearl, 1988), which indicates the presence of a curve. These networks treat each cue as a node in a graphical structure where the connections represent probabilistic relationships. As drivers

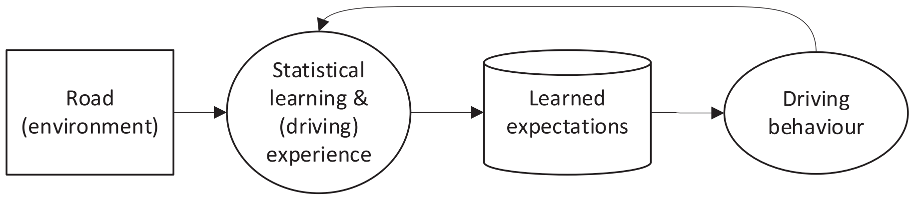

Fig. 1. the assumed influence of statistical learning on driver behaviour (after Theeuwes (2021)).

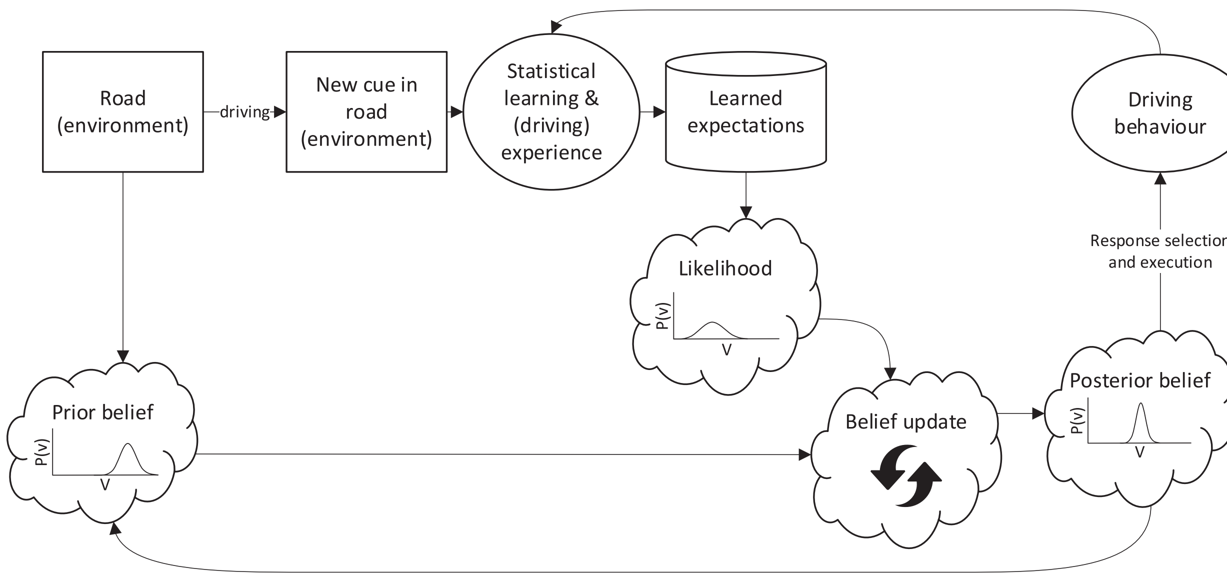

Fig. 2. extending Fig. 1 with Bayesian belief updating. The figure shows how driving along a road provides prior beliefs about safe speeds P(v). When a new cue is encountered, the driver retrieves the corresponding likelihood probabilities from long-term memory. In working memory, the likelihood and the prior belief are combined during the belief-updating process, resulting in a posterior belief about safe speed. Based on this updated belief, drivers adjust their driving behaviour accordingly.

observe various pieces of evidence, the network propagates these updates, refining the overall expectation of the characteristics of the curve.

This iterative process of belief updating is central to the concept of prediction error (Engström et al., 2018). Drivers aim to reduce the discrepancy between their anticipated safe speed and the actual speed required to negotiate a curve safely (Summala, 2007). Vos et al. (2024) demonstrated that the measured speed reductions closely align with the predictions made using a Bayesian model. Conversely, if drivers form inaccurate expectations, for example, underestimating the sharpness of the curve, they may choose an excessively high speed, potentially leading to loss of control, skidding (Torbic et al., 2014), or even crashes.

2.4. *Crash frequency analysis*

Modelling crash risk has long been a method for understanding the relationship between road design elements, driver behaviour, and crash occurrence (Hagenzieker et al., 2014; Montella et al., 2008) and can be used to identify hazardous road locations (Al-Marafi and Somasundaraswaran, 2024). By revealing the complex interactions between drivers' decision-making processes and crash likelihood (Grande et al., 2017; Imprialou et al., 2016), these models provide critical insights into how expectations of curve geometry influence safety. For example, crash frequency models consistently show that the entrance of horizontal curves is the most hazardous segment. This is where drivers must anticipate the curve radius and adjust their speed accordingly, making their expectations of the curve's sharpness a key factor in safety outcomes (Othman et al., 2014).

Research has further highlighted the importance of geometric design in shaping driver behaviour. On two-lane state roads, for instance, curves with radii smaller than 200 m are associated with elevated crash rates because the demand for lateral friction exceeds what drivers can comfortably handle (Maljković and Cvitanić, 2016). These findings emphasise the role of both physical design and driver ability to perceive and anticipate curve geometry in preventing crashes.

Crash data must be retrieved and linked to geometric information in order to explore the relationship between driver expectations and crash outcomes. However, crash data often exhibits characteristics that require careful handling. Crash occurrence is typically nonlinear and better suited to modelling with Poisson or negative binomial distributions. In addition, crash data frequently contains excessive zero counts, which can be addressed using zero-inflated models (Abdulhafedh, 2017; Pew et al., 2020). These models are particularly useful in identifying instances where crashes are unlikely due to low traffic volumes or other factors, such as enforcement activities.

Zero-inflated models consist of two components: a binary process that predicts the excess zeros and a count process that models the nonzero crash counts. The binary process identifies segments with an excess of zeros based on factors such as traffic volume or driver familiarity with the road. The count process accounts for the non-zero crash frequencies by incorporating variables like geometric features, or in this study, driver expectations of curves. By integrating crash data with insights into driver expectations of curves, this study aims to clarify how mismatches between expected and actual curve geometry contribute to crash frequency.

3. Method

This research consists of three main steps, which are illustrated in

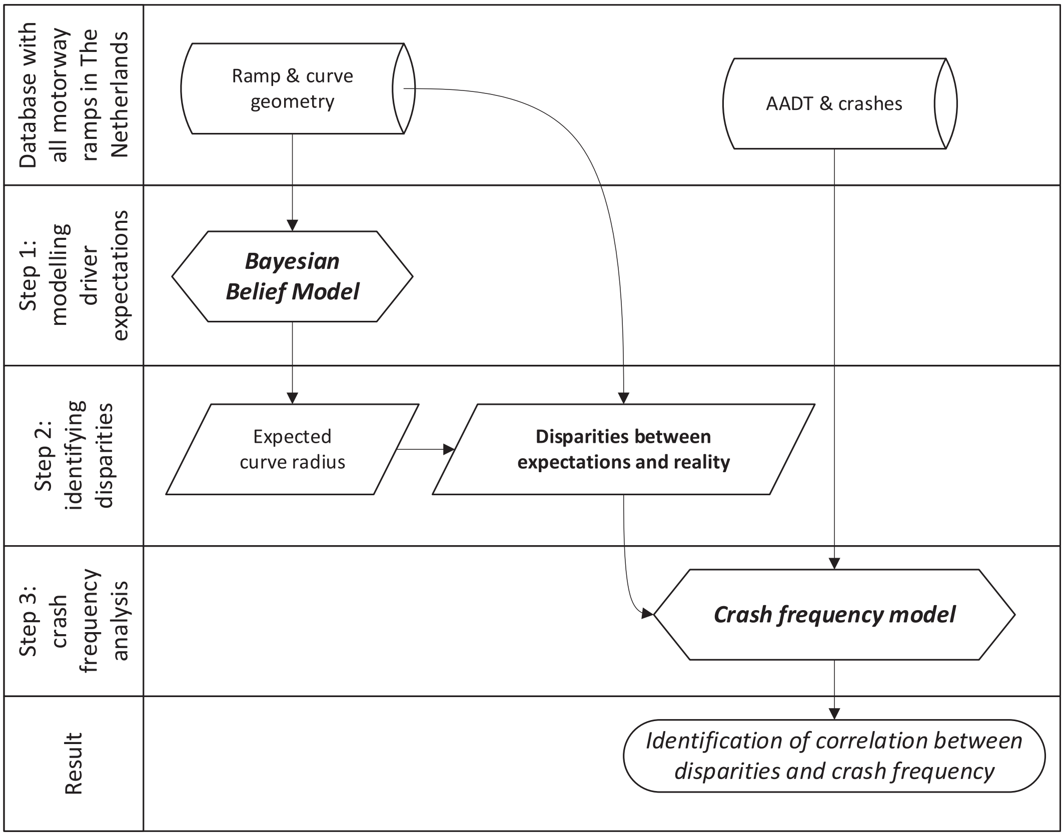

Fig. 3. the framework for analysing disparities in driver expectations and crash frequency.

Fig. 3.

1. Modelling driver expectations: A Bayesian Belief Model is developed to estimate drivers' expected curve radii based on geometric data from a database containing all motorway ramps in the Netherlands.
2. Identifying disparities: The modelled expectations are compared to the actual geometric characteristics of curves, identifying any disparities between drivers' expectations and reality.
3. Crash frequency analysis: The identified disparities are analysed using a crash frequency model, which incorporates additional data on annual average daily traffic (AADT) and crash occurrences. This step evaluates whether disparities between expectations and reality correlate with crash frequency.

This approach identifies correlations between the disparities in expectations and reality and crash frequency.

This section is organised into three parts, explaining the parts shown in Fig. 3. First, the data collection is discussed. Second, it outlines the development of the Bayesian Belief Network, which mimics drivers' expectations, and how this network is used to identify disparities between expectations and reality. Finally, it addresses the analysis of crash frequency to uncover any relationships between expectations, reality, and crash occurrence.

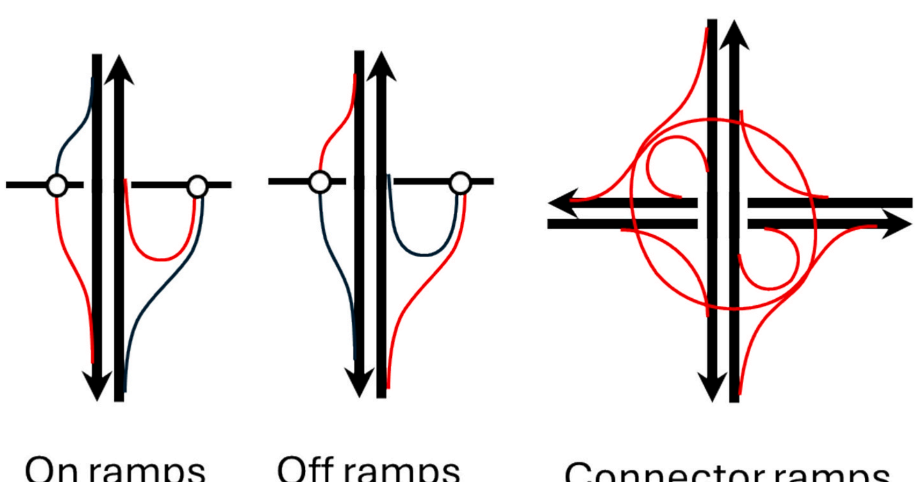

Fig. 4. on and off-ramps are part of intersections to connect lower-level roads to motorways, and connector ramps connect motorways in interchanges.

3.1. Data collection and preparation

This research uses a dataset retrieved from Rijkswaterstaat, the Dutch national road authority. The dataset includes information on all available ramps in motorway junctions in the Netherlands, including on-ramps, off-ramps, and connector ramps. On and off-ramps are part of intersections with lower-level roads, while connector roads are part of interchanges between two motorways, see Fig. 4.

Specifically, the dataset includes 1209 on-ramps, 1220 off-ramps, and 537 connector ramps, totalling 2972 ramps. All on-ramps are preceded by an intersection (an at-grade crossroads controlled by either a roundabout or traffic signals). The off-ramps are preceded by exit lanes (dedicated deceleration lanes that split from the through carriageway) in 76 % of the cases, forks (diverging branches without a separate deceleration lane) in 4 % and by weaving sections (segments in which entering and exiting streams must cross) in 20 % of the cases. The connector ramps are preceded by exit lanes in 39 % of the cases, by forks in 24 %, and by weaving sections in 37 % of the cases. The dataset includes the annual average daily traffic (AADT) and the number of all crashes (fatalities, injuries and damage only) in the period from 2014 to 2018 for all these ramps. Summary statistics can be found in Table 1.

These ramps collectively feature 3940 curves, and their characteristics are detailed in Table 2. A curve is defined as a section that has an angle of at least 10 grad in one direction. That is because the curve angle is a key variable in speed anticipation in curve approach, and 10 grad is a threshold related to the visibility of a curve related to speed reduction (Riemersma, 1988). It is furthermore set as a threshold to distinguish straight sections from curves based on the available data (Ambros and Valentová, 2016).

Since continuous variables can not be combined with categorical variables to construct a Bayesian Belief Network, the horizontal radii and angles have been organised into groups. The horizontal radii have been grouped into intervals representing speed increments of 10 km/h. To accomplish this, a speed prediction model based on Dutch measurements by Vos and Farah (2022) was used to calculate the horizontal radius (R_h) based on a 85th percentile speed ($V85$). This is presented as equation (1):

$$R_h = e^{\frac{v85+62}{28.5}} \tag{1}$$

The angle groups have been classified into three categories, each containing right angles, which are assumed to be recognisable by drivers, because from a distance, a curve becomes a right kink (Brummelaar, 1975). The resulting groups are shown in Table 3.

Since preceding elements are assumed to be crucial in setting expectations, a variable was created to contain the element preceding a curve. This element can either be a discontinuity (exit lane, fork, intersection or weaving section) or a preceding curve, which are gathered from the database.

3.2. Modelling expectations

To model drivers' expectations, a Bayesian Belief Network (BBN) is built, as explained in the literature review, using the data of all Dutch connector road curves as learning input. BBN's are essentially acyclic graphs, where nodes represent random variables and connections show direct probabilistic links between them.

In a BBN, the influence typically flows from parent nodes to child nodes. This means that the state of a parent node affects the likelihood of the child node being in a certain state. When a node (or variable) is observed by a driver, it is called evidence. By observing this evidence, the probability distribution can be updated towards certainty and pass this updated information through the network. This process modifies the probability distribution of other nodes (i.e. the other variables and expected radius).

So, in simpler terms, a BBN can be used to statistically model expectations about radii. This is done by treating them as posterior beliefs based on observed evidence of variables on curves. The dataset provides the input to learn the BBN, resembling how drivers learn expectations through multiple experiences, because the dataset contains available cues a driver observes.

The modelling and analysis were executed using the GeNIe Modeler ("GeNIe Modeler," 2022), an interface for the Structural Modelling, Inference, and Learning Engine (SMILE) (Druzdzel, 1999). This interface enables the dataset to be used for learning and evaluating BBNs.

Since various variables are interconnected, such as the co-occurrence of intersections as preceding elements on on-ramps or the tendency for forks to have more lanes than deceleration lanes, their interdependence needs to be explored. To investigate these interdependencies, the Tree Augmented Naïve Bayes (TAN) structure was employed, which learns interdependencies from the dataset's interconnections, using a likelihood sampling algorithm – Maximum Likelihood Estimation (MLE). So, the generated conditional probability distributions are created purely data-driven and provide the estimation of the parameters the TAN uses. The TAN algorithm establishes connections between variables to address dependence (Friedman et al., 1997), particularly in relation to the expected radius. The strength of influence is measured in the GeNIe Modeler by calculating the average Euclidean distance between the expected radius and the variables (Koiter, 2006). This measurement indicates how much one variable influences the probability of another variable.

3.3. Testing the relationship between expectations and crashes

The created TAN is believed to mimic drivers' expectations regarding the horizontal radius of an upcoming curve. The model has learned relationships from the dataset, establishing probabilistic links between curve radius and available cues. The TAN is used to predict curve radii for two situations. First, general cue combinations are provided as evidence to the TAN. The predictions of the TAN reflect the expectations drivers are assumed to have when faced with these cues. This establishes a baseline for road design and safety assessment, to keep the disparity between expectations and reality as low as possible.

Next, the TAN uses the specific cues per curve in the database to predict the drivers' expectations per curve approach. This process identifies the gaps between the actual and expected curve radii for each curve, as illustrated in Fig. 3. The differences are calculated in terms of speed, as curve radii are grouped by 10 km/h intervals. Negative values indicate that drivers expect lower speeds than what the curve offers, while positive values indicate higher speed expectations than what the curve supports.

The disparity between expected and actual speed in curves serves as an independent variable in a crash frequency model. Given that the data includes numerous zeros (as shown in Table 1), a variety of statistical distributions, such as Poisson and negative binomial, with and without a zero-inflated component, are employed to analyse the relationship

Table 1
summary statistics of the ramp data.

Characteristic	Minimum	1st quantile	Median	Mean	3rd quantile	Maximum
AADT	100	2800	4800	7369	8900	68,367
Crashes (2014 – 2018)	0	0	1	3.1	3	115

Table 2
summary statistics of the geometry of the curves in the database.

Characteristic	Minimum	1st quantile	Median	Mean	3rd quantile	Maximum
Horizontal radius (m)	12	84	184	303	352	5526
Angle (grad)	10	22	49	81	106	349
Number of lanes	1	1	1	1.2	1	5

Table 3
summary of horizontal radius groups and curve angle groups.

Horizontal radius group (m)	Representing 85th percentile speeds (km/h)	N	%	Curve angle group (grad)	N	%
0 – 35	0 – 40	96	2 %	10 – 100	2882	73 %
35 – 50	40 – 50	241	6 %	100 – 200	562	14 %
50 – 70	50 – 60	407	10 %	200 – 350	485	12 %
70 – 105	60 – 70	518	13 %			
105 – 145	70 – 80	349	9 %			
145 – 205	80 – 90	530	13 %			
205 – 295	90 – 100	551	14 %			
295 – 415	100 – 110	441	11 %			
415 – 595	110 – 120	298	8 %			
595 – 840	120 – 130	218	6 %			
840 – 1200	130 – 140	150	4 %			
> 1200	> 140	130	3 %			

between the disparity in speed and crashes. The average annual daily traffic (AADT) is also used as a variable to account for the large number of zeros, as depicted in Table 1. By employing different models, the results can be cross-validated.

4. Results

The results of this research are presented in two main parts. First, the results of the Bayesian Belief Network are presented, followed by the results of the crash frequency modelling.

4.1. Bayesian belief network to mimic driver expectations

As a baseline, the database was used to construct a Naïve Bayesian Belief Network (NBN) with the horizontal radius serving as the class variable. In this configuration, the other variables (roadway type, preceding element, number of lanes, and curve angle) act as child variables of the horizontal radius, without any interdependencies among them. This network achieved an Expectation-Maximisation (EM) Log Likelihood of −26,121.8.

Next, a Tree Augmented Naïve Bayesian Network (TAN) was learned using the same data, which allows for interdependencies among the child variables, in line with reality. This approach resulted in the network depicted in Fig. 5, with an improved EM Log Likelihood of −24,103.7. This higher log likelihood indicates a better fit compared to the NBN, suggesting that the TAN more accurately models driver expectations. Other learning algorithms, such as Bayesian Search and Greedy Thick Thinning, all produced networks with inferior fits.

The strength of influence for the nodes in the TAN are presented in Table 4.

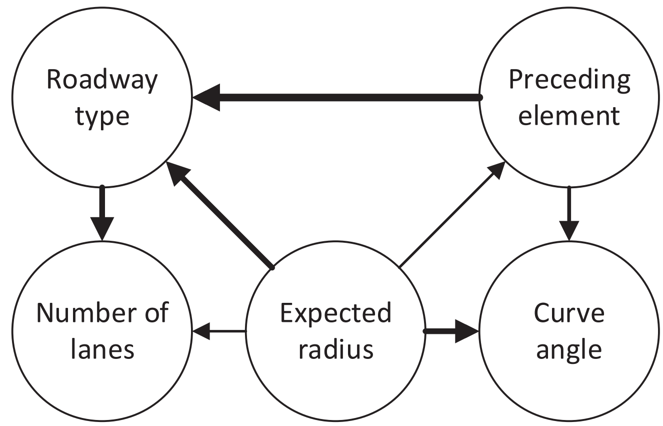

Fig. 5. the learned Tree Augmented Naive Bayesian Network. The arrows (nodes) represent the modelled relations between the variables. The thickness of the arrows represents the average strength of the influence, given in Table 4.

Table 4
Average strength of influence for each node in the TAN.

Parent	Child	Average strength of influence
Preceding element	Roadway type	0.342066
Category of horizontal curves	Category of curve angle	0.304285
Roadway type	Number of lanes	0.291780
Category of horizontal curves	Roadway type	0.284438
Preceding element	Category of curve angle	0.179947
Category of horizontal curves	Number of lanes	0.106685
Category of horizontal curves	Preceding element	0.106455

4.1.1. Modelled driver expectations given certain road layouts

The trained TAN was used to forecast the expected horizontal radius given the type of roadway, the preceding element, the number of lanes, and the angle of the curve. These are parameters that designers typically have access to in the early stages of design, allowing them to anticipate what drivers expect of the sharpness of an upcoming curve. The TAN assigns a probability to each curve group, essentially reflecting a range of beliefs about the curves' radius. Fig. 6 provides an example of how the TAN generates these probabilities given specific cues.

As shown in Fig. 6, the TAN does not predict a single curve group, but instead assigns probabilities to a range of groups. To help designers anticipate the most likely driver expectations based on specific cues, Table 5, Table 6, and Table 7 present typical combinations of cues for connector roads, off-ramps, and on-ramps, respectively. The tables provide the range of horizontal radii predicted by the TAN as well as the corresponding range of 85th percentile speeds, based on equation (1). The expected radius range represents the curve group with the highest probability, given the cues provided in the table. If the probabilities of adjacent curve groups differ by less than 5 %, they are also included in the expected curve group. For example, in Fig. 6, the expected curve radius group ranges from 205 to 415 m, indicating an expected 85th

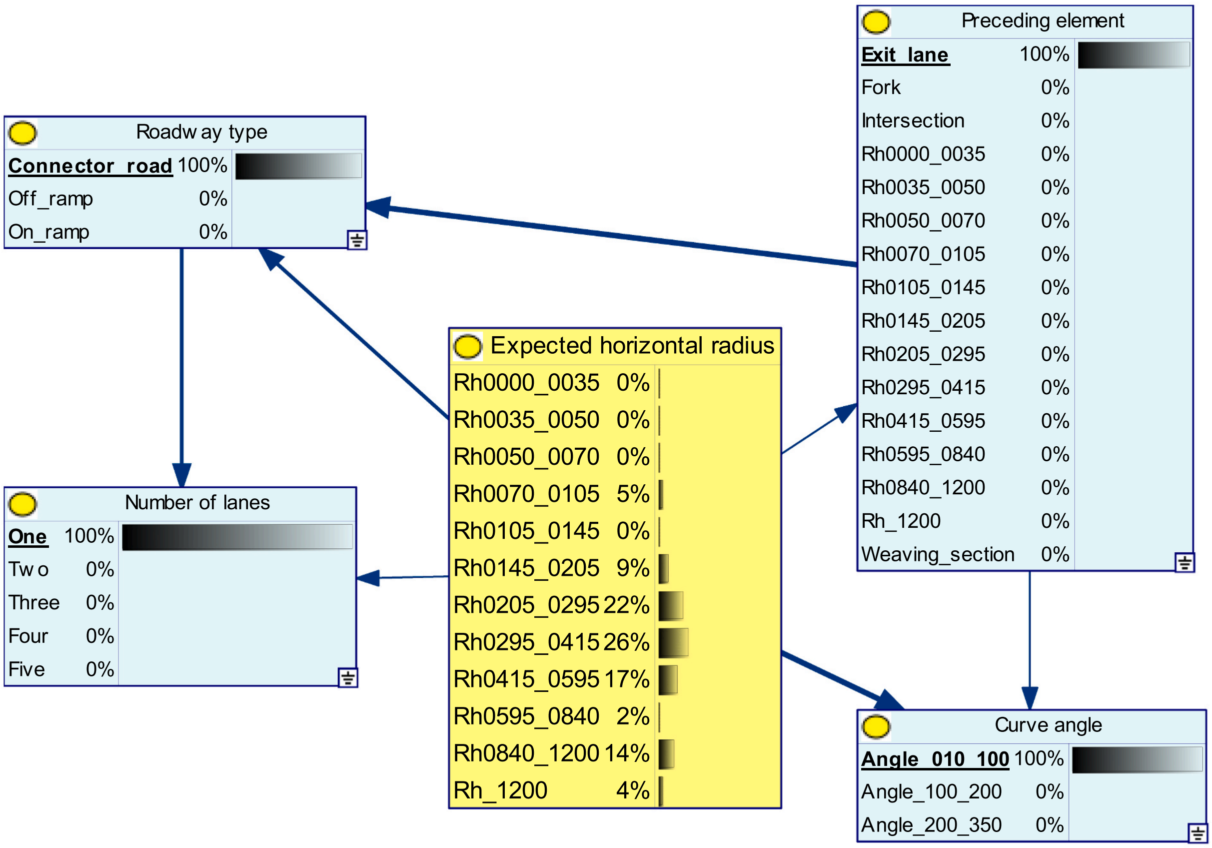

Fig. 6. This TAN shows observed cues by setting the probability of these cues to 100%. This example is a roadway which is a connector road with one lane, preceded by an exit lane and an angle between 10 and 100 grad. Given these cues, the TAN shows that the probabilities of the expected horizontal radii are mostly between 145 and 595 m, with a mode in the group of radii between 295 and 415 m.

percentile speed between 90 and 110 km/h. This is represented in the first line of Table 5.

4.1.2. Differences between predicted and actual radii

To provide the expected curve radii for each of the available curves in the database, the TAN is used to determine the most probable curve range, given the available cues. The results of this analysis are presented in Table 8 as a confusion matrix.

The confusion matrix shows that 28 % of the curves in the database match the expectations that drivers are assumed to have built based on all the motorway ramp curves available in the Netherlands exactly, and 58 % within a range of 10 km/h higher or lower than expected.

Using the outcomes of the TAN, the actual horizontal radius and the predicted horizontal radius are both converted to 85th percentile speeds, using equation (1). Next, the difference between the predicted (i.e. expected) speed and the actual speed related to the curves' radius is calculated, which results in a mean difference of −2.3 km/h (SD = 21.3 km/h) for the dataset. A negative value represents a lower expected radius (i.e., lower speed) than is available, while a positive value indicates a possible misleading situation representing a higher radius and higher speed than available. This variable is tested on actual crash data in the next paragraph.

4.2. Crash frequency related to expectations and curve radii

Crashes resulting from a mismatch between expected and actual curve radii are assumed to be related to speed reduction. Consequently, curves that do not require a speed reduction are excluded from the dataset. According to equation (1), curves with radii greater than 840 m are filtered out because the 85th percentile speed on these curves is 130 km/h, which matches the legal speed limit on motorways in the Netherlands. This filtering process yields a dataset of 3649 curves suitable for modelling crash frequency.

Table 1 reveals that many road segments in the database have zero accidents, suggesting a distribution of accidents that is skewed towards zero and potentially over-dispersed. To address this issue, various methods discussed in section 2.3 are used to model crash frequency. Poisson, negative-binomial (NB) and zero-inflated models are evaluated, but the intercept-only zero-inflated negative binomial regression (ZINB) did not improve fit over the plain NB (AIC 18119.9 vs 18117.9), indicating no zero-inflation beyond what the NB already accommodates. The NB model itself predicts 1363 zeros versus 1171 observed (ratio = 0.86), signifying zero-deflation rather than excess zeros. By contrast, the Poisson fit predicts only 120.7 zeros (ratio = 9.7), massively under-predicting zeros ($p < 2.2 \times 10^{16}$) and yielding a much poorer AIC (37310.1 vs 18117.9 for NB). Accordingly, Table 9 presents Poisson (to illustrate its zero under-fit), NB (to capture overdispersion without inflation) and zero-inflated Poisson (ZIP, to accommodate the excess zeros that Poisson alone misses).

All the models in Table 9 demonstrate a positive correlation between the difference in expected and actual speeds and crash frequency. This indicates that when the expected speed is higher than the actual speed, crash frequencies tend to increase. Among the five models, the negative-binomial model with AADT achieves the best overall fit by information criteria and log-likelihood, reflecting its ability to capture over-dispersion without over-penalising complexity. The Poisson model with ln(AADT), by contrast, delivers the highest pseudo-R^2 (0.368) and lowest RMSE (5.80), but at the cost of a larger AIC and BIC, indicating substantial under-dispersion penalised in information-criterion terms. The ZIP specification sits between them, successfully modelling excess

Table 5
cues for curves in connector roads, and the expectations generated by the TAN as a range of horizontal radii and 85th percentile speeds.

Cues			Expectation	
Preceding element	**Number of lanes**	**Angle (grad)**	**Modal R_h (m)**	**V85 (km/h)**
Exit lane	1	0–100	205–415	90–110
Fork			415–595	110–120
Weaving section			205–595	90–120
R_h 205–295 m			205–295	90–100
R_h 295–415 m			295–415	100–110
R_h 415–595 m			205–840	90–130
R_h 595–840 m			415–595	110–595
R_h > 1200 m			295–415	100–110
Exit lane	2		295–415	100–110
Fork			415–595	110–120
Weaving section			205–595	90–120
R_h 205–295 m			205–595	90–120
R_h 295–415 m			295–840	100–130
R_h 415–595 m			205–840	90–130
R_h 595–840 m			415–595	110–120
>1200 m			295–595	100–120
Fork	3		415–595	110–120
Weaving section			>1200	140
R_h 415–595 m			595->1200	120–140
R_h 595–840 m			415–1200	110–130
R_h 840–1200 m			415->1200	110–140
R_h > 1200 m			>1200	140
Exit lane	1	100–200	70–105	60–70
Fork			70–105	60–70
Weaving section			70–105	60–70
R_h 70–105 m			70–105	60–70
R_h > 1200 m			70–105	60–70
Exit lane	2		70–105	60–70
Fork			205–415	90–110
Weaving section			70–105	60–70
R_h 70–105 m			205–295	90–100
R_h 205–295 m			295–415	100–110
R_h 295–415 m			205–295	90–110
R_h > 1200 m			295–415	100–120
Exit lane	1	200–300	70–105	60–70
Fork			70–105	60–70
Weaving section			70–105	60–70
R_h > 1200 m			50–70	50–60

zeros but still underperforming in AIC/BIC. As for the main predictor, the difference in expected and actual speeds is statistically insignificant in both NB models, yet attains significance in the Poisson regressions and the ZIP count component. After adjusting for AADT, every 10 km/h greater discrepancy between expected and actual speeds is associated with a 3.8 % increase in annual crash counts in the Poisson model ($\beta = 0.037$, $p < 0.001$) and a 2.7 % increase in the zero-inflated Poisson model ($\beta = 0.027$, $p < 0.001$).

Since the horizontal radius is known to influence crash frequency, a sensitivity analysis was performed using the same set of models, this time with the horizontal radius as the independent variable instead of the speed difference. The results of this analysis are presented in Table 10. Note that the positive radius coefficient in models without AADT reflects that gentler curves tend to occur on higher-volume roads, whereas once AADT is included, the coefficient becomes negative. This reveals that, at a given traffic volume, tighter curves (smaller radii) lead to higher crash counts, which is in line with literature.

Because large-angle curves are underrepresented, the dataset was split into three curve-angle bins – 0–100, 100–200, and 200–350 grad – to assess how underrepresented, high-angle curves affect model performance. For each subset and for the full dataset, the trained TAN was used to predict the expected speed, then calculated the Mean Absolute Error (MAE) between predicted and actual speeds and accident risk, defined as crashes per 1000 AADT. The results appear in Table 11.

Table 6
cues for curves in off-ramps, and the expectations generated by the TAN as a range of horizontal radii and 85th percentile speeds.

Cues			Expectation	
Preceding element	**Number of lanes**	**Angle (grad)**	**Modal R_h (m)**	**V85 (km/h)**
Exit lane	1	0–100	145–295	80–100
Weaving section			145–295	80–100
R_h 145–205 m			105–295	70–100
R_h 205–295 m			70–205	60–90
R_h > 1200 m			145–295	80–100
Exit lane	2		145–295	80–100
Weaving section			145–205	80–90
R_h 145–205 m			145–205	80–90
R_h 205–295 m			145–205	80–90
R_h > 1200 m			145–205	80–90
Exit lane	1	100–200	50–105	50–70
Weaving section			50–70	50–60
R_h 50–70 m			35–50	40–50
R_h 70–105 m			70–105	60–70
R_h > 1200 m			70–105	60–70
Exit lane	2		70–105	60–70
Weaving section			105–145	70–80
R_h 70–105 m			70–105	60–70
R_h 105–145 m			35–50	40–50
R_h > 1200 m			70–105	60–70
Exit lane	1	200–300	70–105	60–70
Weaving section			70–105	60–70
R_h > 1200 m			70–105	60–70

Table 7
cues for curves in on-ramps, and the expectations generated by the TAN as a range of horizontal radii and 85th percentile speeds.

Cues			Expectation	
Preceding element	Number of lanes	Angle (grad)	Modal R_h (m)	V85 (km/h)
Intersection	1	0–100	145–595	80–120
R_h 145–205 m			145–205	80–90
R_h 205–295 m			145–205	80–90
R_h 295–415 m			145–205	80–90
R_h 415–595 m			205–415	90–110
R_h > 1200 m			145–295	80–100
Intersection	2		205–595	90–120
R_h 205–295 m			105–295	70–100
R_h 295–415 m			145–205	80–90
R_h 415–595 m			295–415	100–110
>1200 m			205–295	90–100
Intersection	1	100–200	50–105	50–70
R_h 50–70 m			35–50	40–50
R_h 70–105 m			70–105	60–70
R_h > 1200 m			35–50	40–50
Intersection	2		70–105	60–70
R_h 70–105 m			70–105	60–70
R_h > 1200 m			35–50	40–50
Intersection	1	200–300	50–70	50–60
R_h > 1200 m			35–50	40–50

There is a clear upward trend in both MAE and accident risk as curve angle increases, indicating that sharper, less common curves are predicted less accurately and coincide with higher crash frequencies.

To further test the sensitivity of the bin-sizes, bin sizes of 5 km/h were also modelled and compared to the original 10 km/h bins. The EM algorithm's log-likelihood for the 5 km/h–binned TAN (–26 490) is substantially lower than for the original 10 km/h version (–24 103), indicating that halving the bin width – while doubling the number of parameters – actually worsens overall model fit, indicating worse predictability of curve speeds. To further validate this choice, the regression

Table 8
confusion matrix for the predicted horizontal radius (Rh) by the TAN and the actual horizontal radius.

		Predicted Rh (m)											
		0–35	35–50	50–70	70–105	105–145	145–205	205–295	295–415	415–595	595–840	840–1200	>1200
Actual Rh (m)	0–35	10	17	15	29	5	2	17	0	1	0	0	0
	35–50	0	85	69	29	5	19	32	1	1	0	0	0
	50–70	2	48	195	56	10	30	63	3	0	0	0	0
	70–105	3	12	104	156	24	79	124	11	3	1	0	1
	105–145	0	2	26	53	34	85	135	10	2	2	0	0
	145–205	0	2	15	31	21	173	258	23	6	1	0	0
	205–295	0	1	2	22	16	131	313	46	16	4	0	0
	295–415	0	0	2	6	16	114	191	89	15	8	0	0
	415–595	0	0	0	7	6	50	142	51	35	4	0	3
	595–840	0	0	0	1	3	43	122	24	9	12	0	4
	840–1200	0	0	0	1	2	33	69	28	13	1	0	3
	>1200	0	0	0	1	1	23	60	28	9	2	0	6

Table 9
Results of crash frequency modelling on the difference between expected and actual speeds in curves.

	Negative binomial regression		Poisson regression		Zero-inflated Poisson regression
Constant	1.184***	−0.729***	1.184***	−1.114***	
	(0.025)	(0.047)	(0.009)	(0.028)	
Difference between expected and actual speed (10 km/h)	0.012	0.013	0.010*	0.037***	0.028***
	(0.013)	(0.011)	(0.005)	(0.005)	(0.005)
ln(AADT)		0.962***		1.155***	−0.271***
(1000 vehicles/day)		(0.024)		(0.011)	(0.016)
Constant of difference between expected and actual speed (10 km/h)					1.539***
					(0.009)
Constant of ln(AADT)					0.678***
(1000 vehicles/day)					(0.079)
R2	0.001	0.106	0.001	0.368	0.075
R2 Adj.	0.000	0.105	0.000	0.368	0.074
Log-likelihood	−8233	−7365	−16410	−10375	−13988
AIC	16473.7	14738.1	32824.3	20755.9	27984.2
BIC	16492.3	14762.9	32836.7	20774.5	28009.0
RMSE	7.38	6.05	7.38	5.80	7.14
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001					

Table 10
Results of crash frequency modelling on the horizontal radius of curves.

	Negative binomial regression		Poisson regression		Zero inflated Poisson regression
Constant	0.846*** (0.039)	−0.717*** (0.049)	0.893*** (0.015)	−1.096***(0.028)	
Radius of horizontal curve / 100 (m)	0.140***(0.013)	−0.007(0.011)	0.120***(0.004)	−0.026***(0.005)	0.116***(0.005)
ln(AADT)		0.965***		1.178***	1.098***
(1000 vehicles/day)		(0.024)		(0.012)	(0.053)
Constant of radius of horizontal curve /100 (m)					1.254***
					(0.016)
Constant of ln(AADT)					0.665***
(1000 vehicles/day)					(0.079)
R2	0.006	0.105	0.021	0.367	0.160
R2 Adj.	0.006	0.105	0.021	0.367	0.160
AIC	16372.1	14790.1	32147.9	20783.0	27414.7
BIC	16390.7	14814.9	32160.3	20801.6	27439.5
Log-likelihood	−8183	−7366	−16071	−10388	−13703
RMSE	7.35	6.07	7.34	5.81	7.10
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001					

Table 11
Mean Absolute Error and Accident Risk by curve angle group.

Curve angle group	MAE (km/h)	Accident risk (accidents / AADT / 1000)
Full set	16.11	0.48
Angle group 010–100 grad	18.56	0.45
Angle group 100–200 grad	25.59	0.52
Angle group 200–350 grad	37.61	0.58

analysis was re-run using the 5 km/h bins. In the base negative-binomial and Poisson models, the finer binning yields only modest improvements in AIC and log-likelihood, and in the AADT-augmented versions, it produces no gain or even slight deterioration, while RMSE remains essentially unchanged across all specifications. Taken together, these mixed outcomes – and the fact that the 10 km/h bins deliver comparable or better parsimony (fewer parameters) and predictive stability – reinforce that the original 10 km/h intervals strike a good balance.

5. Discussion and limitations

This research demonstrates how incorrect expectations of curve radii contribute to higher crash frequencies, providing a broader perspective than traditional geometric design consistency studies. It helps to understand the cues which play a role in building the drivers' expectations and how these expectations can contribute to crash risks.

The results suggest that traditional design consistency measures, such as speed differentials (Lamm et al., 1999), may not fully capture the complexities of driver behaviour. Instead, incorporating probabilistic models can improve our understanding of driver expectations (Vos et al., 2024). The Tree Augmented Naïve Bayesian Network (TAN) shows the intricate nature of curve expectations. The strength of the variables' influences indicates the extent to which expectations are shaped by the roadway type and preceding elements. This finding aligns with the self-explaining road principle, which suggests that road users can immediately understand how to behave and what to expect on roads, based on unique road layouts (Theeuwes, 2021). It furthermore underpins that drivers have expectations about a suitable speed, based on road features and surroundings, as shown by Charlton and Starkey (2017).

Using the TAN model to gain insight into the expectations of drivers, Table 5, Table 6, and Table 7 show that drivers expect larger radii in connector ramps compared to on and off-ramps. Besides that, drivers expect a larger radius – and hence a higher speed – when encountering a more gradual curve angle. This observation aligns with insights derived from the perspective analysis of curves (Fildes and Triggs, 1985; Riemersma, 1988).

The TAN model was trained using the entire dataset to predict the expected radii of curves. While this approach deviates from the common practice of splitting data into training and testing sets, it aligns with the goal of this research, which is to replicate drivers' expectations. Similar to how humans create schemas in their memory (Ghosh and Gilboa, 2014), drivers form their expectations based on all available experiences. Additionally, it is unrealistic to assume that Dutch drivers have encountered every Dutch motorway curve, as the TAN model has. The TAN model, therefore, does not take into account how familiarity influences driving behaviour (Harms et al., 2021). Nonetheless, the TAN model is believed to provide a representative average of Dutch motorway curve expectations. So, while the presented data is only representative of Dutch motorways, the presented methodology is applicable in other regions, assuming that the local data is available. Future research should explore how different environmental and contextual factors influence Bayesian updating in real-world driving conditions.

The results from the crash frequency analysis confirm that disparities between expected and actual speeds in curves are associated with increased crash frequency, reinforcing the importance of design consistency and driver expectations in road safety. These findings align with existing literature, which emphasises that unexpected geometric changes can disrupt driver anticipation, leading to higher crash risks (Montella et al., 2008; Othman et al., 2014). The observed relationship between speed disparities and crash occurrences supports the notion that driver adaptation to unexpected curve geometries plays a critical role in crash outcomes.

Crash data, by nature, are count-based and often display overdispersion (i.e., the variance exceeds the mean) and an excessive number of zero counts. A Poisson regression was considered due to its simplicity and common application in count data analysis. However, the Poisson model assumes equality of mean and variance, which is often violated in crash data. To address overdispersion, a Negative Binomial regression was employed, which introduces an additional parameter to model the variance independently of the mean. Furthermore, the high incidence of zero crashes motivated the use of a Zero-Inflated Poisson (ZIP) model, because the Poisson fit underpredicted zeros in the dataset. Zero-Inflated models assume that the zeros in the data arise from a separate process (e.g., road segments where crashes are inherently unlikely) in addition to the regular count process. However, common underreporting of crashes might skew the results of the ZIP. Possible improvement of the dataset to overcome this would include police reports or insurance data. By comparing all the models using metrics such as log-likelihood, AIC, BIC, and RMSE, both the fit and predictive performance were evaluated. This multi-model approach not only cross-validates the observed associations but also ensures that the chosen model aligns well with the underlying data characteristics, as supported by previous studies (Abdulhafedh, 2017; Pew et al., 2020).

When analysing the various crash frequency models developed in this research, several observations can be made. Only the Poisson regression models show a significant correlation between crash frequency and the difference in expected and actual speed. However, the Poisson regression models have higher AIC and BIC values than the negative binomial models, indicating that the Poisson regression is a more complex model type. Furthermore, all models indicate that AADT has a greater influence on crash frequency than the difference in expected and actual speeds. This could be explained by the relatively high self-explanatory characteristics of Dutch motorways (Theeuwes, 2021; Walker et al., 2013). As a result, crash risk on Dutch motorways is less dependent on driver expectations and more influenced by traffic volume. Possibly even adding other variables like heavy vehicle proportions, weather conditions, or driver experience might shift the exact correlation, but still, the results show that when deviating from expectations, crash risk increases. This makes sense, because when the expected suitable or correct speed (Charlton & Starkey, 2017) is overestimated, drivers are prone to loss of vehicle control, such as skidding (Torbic et al., 2014), oversteering or running off the road.

In the data of all Dutch motorway ramp curves, an imbalance in curve angle groups (with the majority falling within the 10–100 grad range) is acknowledged as reflecting real-world conditions, where drivers most frequently encounter these curve types. This imbalance allows the model to robustly capture general trends in driver expectations for common curve angles, aligning with how drivers form expectations based on frequent experiences. The analysis of the specific subgroups of curve angles indeed shows that the more uncommon, large-angle curves have increased Mean Average Error, indicating worse predictability and increased crash risk. This is in line with the crash frequency analysis.

It is important to note that while the analysis based on the difference between expected and actual speeds provides insights into the role of driver behaviour, sensitivity analysis using the horizontal radius – a well-established indicator of crash risk – offers additional perspective. The results in Table 10 reveal that the horizontal radius of curves is significantly related to crash frequency across all model types, when controlling for AADT. This finding underscores that inherent road geometric features remain a fundamental determinant of safety. Non-standard or atypical geometries may be less safe for reasons beyond the driver's expectations alone. In this context, although deviations from the expected speed contribute to crash risk, the established influence of road geometry as reflected by horizontal radius remains a critical factor in crash prediction.

From a practical standpoint, these results highlight the necessity of incorporating driver expectations into road design to minimise speed discrepancies at curve entries. Proactively addressing such discrepancies through improved signage, speed advisories, or geometric modifications can enhance safety. Additionally, predictive models can be utilised to identify high-risk locations where interventions should be prioritised.

By integrating human factors knowledge, statistical learning principles, and Bayesian inference, road design can shift towards a more predictive, driver-centred approach. This aligns with broader efforts to create road environments that intuitively guide drivers toward safe behaviour, minimising errors and improving overall traffic safety.

Future research could incorporate driving simulator studies or naturalistic driving data to directly assess how expectation mismatches influence driver behaviour, such as speed adaptation and braking.

Additionally, microsimulation models or surrogate safety measures (e.g., abrupt decelerations, lane departures) could help validate the relationship between expectation disparities and crash risk.

6. Conclusions and application

This research proposes considering a new variable in the assessment of motorway ramp curve safety. It suggests analysing the difference between the expected radius and the actual radius. To accomplish this, a Bayesian Belief Model (BBN) was learned to mimic drivers' expectations of a curve's radius using other visual cues than the radius itself, which itself is not perceivable by the drivers. The model was trained using data from all curves in Dutch motorway ramps, resembling how drivers learn their expectations based on multiple experiences.

A key outcome of this research is the positive answer to the research question: does a mismatch of drivers' expectations of motorway ramp curves align with safety implications? The findings clearly indicate that when drivers expect a larger radius than the actual curve (i.e., when they expect the curve to be less sharp than it is), crash frequency increases. This relationship substantiates the hypothesis that discrepancies between expected and actual curve geometry are significant predictors of safety risks.

The study's main insights include:

- Disparity and crash frequency: The analysis shows that as drivers expect a curve to be less tight than it actually is, crash frequency increases. This is therefore a novel variable for roadway design consistency analysis.
- Practical safety metrics: The BBN outputs an expected curve radius from upstream visual cues. When compared with the actual design, this difference becomes a quantifiable metric for assessing safety. Detailed expectations and associated operating speeds are provided in Table 5, Table 6 and Table 7, while Table 9 links these disparities to crash frequency models.

Based on these insights, two key applications emerge:

- Proactive Design: Engineers and policymakers can integrate the expectation-versus-actual curve disparity into the design phase. Adjusting design elements to more closely match driver expectations using Table 5, Table 6 and Table 7 can help prevent the risk of crashes. Specifically, design guidelines can mention which curve radii match the driver's expectations, given the relations mentioned in these tables.
- Reactive Policy: For existing hazardous curves, evaluating these discrepancies can pinpoint design features that require improvement. Modifying discontinuity types or other upstream cues can better align driver expectations with actual geometry, thereby mitigating accident risk.

In summary, incorporating the difference between expected and actual ramp curve radii into motorway design provides a valuable metric for enhancing motorway safety. By aligning design elements more closely with driver expectations, it is possible to reduce the likelihood of crashes and improve overall road safety. These contributions offer significant potential for proactive safety interventions and continuous improvement in transportation research and practice.

Statement

During the preparation of this work the author used ChatGPT in order to improve the readability of this work. After using this service, the author reviewed and edited the content as needed and takes full responsibility for the content of the publication.

CRediT authorship contribution statement

Johan Vos: Writing – original draft, Software, Visualization, Resources, Investigation, Conceptualization, Writing – review & editing, Validation, Formal analysis, Methodology, Data curation.

Declaration of competing interest

The author declare the following financial interests/personal relationships which may be considered as potential competing interests: Johan Vos reports a relationship with Rijkswaterstaat that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The aggregated data used in this research is available as: Vos, Johan (2025): Design information, AADT and accidents on Dutch motorway ramp curves. Version 1. 4TU. ResearchData. dataset. https://doi.org/10.4121/ef2fe812-1024-4064-85a9-3853b4cf3462.v1.

The Tree Augmented Naïve Bayesian Network shown in Fig. 6 is available on the BayesFusion Interactive Model Repository and can be used interactively via: https://repo.bayesfusion.com/network/permalink?net=Small+BNs%2FAggregated+Curves+v85.xdsl.

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