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Modelling driver expectations for safe speeds on freeway curves using Bayesian belief networks

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ABSTRACT

Sharp curves in freeways are known to be unsafe design elements since drivers do not expect them. It is difficult for drivers to estimate the radius of a curve. Therefore, drivers are believed to use other cues to decelerate when approaching a curve. Based on previous successful experiences of driven speeds in curves, drivers are thought to have built expectations of safe speeds given certain cues, minimalising risks. This research employs a Bayesian Belief Network to model driver expectations using measured speeds in 153 curves and data on the characteristics of the curve approaches. This model mimics expectations as the probability of measured speeds given certain cues. Using Bayes theorem, prior beliefs on safe speeds are updated towards a posterior belief when a new cue is observed during curve approach. We refer to this posterior belief as expected safe speed. Drivers are assumed to adjust their operating speed if it does not match their expected safe speed. The model shows that the visible deflection angle has a large influence in setting the expectations of a safe speed for an upcoming curve. In addition, the preceding type of roadway and the number of lanes are both important cues to set a driver's expectations of a safe speed. Speed and warning signs are shown to be interdependent on the road scene and hence have less influence in setting expectations. This research shows that design and safety assessment of freeway curves should be considered aligned with the road scene upstream of the curve.

1. Introduction

Both in research and in policy making, there is an increasing interest in a pro-active road safety assessment, based on infrastructure, its surroundings and human factors knowledge, i.e. how drivers interact with the road (Domenichini et al., 2022; SWOV, 2018). Sharp curves in freeways are known to be unsafe design elements, especially when drivers do not expect them (Davidse and Duijvenvoorde, 2020; Elvik, 2022). Research on the interaction between curve characteristics and driver behaviour in the curve *itself* are available and can be used in pro-active assessment of road design and safety (Charlton, 2007; Jamson et al., 2015; Lappi and Lehtonen, 2012; Ryan et al., 2022). Driving task descriptions for curve driving however indicate that drivers anticipate a curve *well ahead* of the start of the curve, by using visual cues on the road to recognize an upcoming curve and using signage to estimate a needed speed change in order to drive safely in the curve (Campbell et al., 2012). The estimation of a safe speed in curves is thought to be based on drivers' judgement of driving comfort and the ability to slow down safely without skidding (Gibson and Crooks, 1938; Summala, 2007). Since drivers start anticipating the curve well ahead of the curve start itself, they are assumed to have *expectations of safe speeds* based on the visual cues they receive during curve approach, such as roadside signs and the road scene upstream of the curve (Campbell et al., 2012). These expectations are believed to be stored in memory schemata of drivers (Charlton and Starkey, 2017b), connecting road characteristics to safe speeds. Quantitative research of speed behaviour in curve approach is covered in deceleration models (Nama et al., 2020), but these models do not take into account the visual cues drivers use during curve approach. They merely show correlations between deceleration and the curve geometric design elements itself. Our aim is to develop a generalizable and quantifiable method to model drivers' expectations during curve approach. This will help to explain which visual cues drivers use to decelerate and that can be used pro-actively in road-design and road safety assessment.

To build such a generalizable and quantifiable model, we first identify which cues are known to influence driving speed behaviour during curve approach (Section 2). We then proceed by discussing how these cues are perceived by drivers and how they build expectations on

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certain safe speeds in curves. Next, we show how to model these expectations using a Bayesian approach. This approach is suitable since it is assumed to resemble how drivers build-up and update their expectations of safe speeds during curve approach. Section 3 of this paper discusses the data and methods used for developing the Bayesian model using the data gathered by Vos et al. (2021b). This data is used since it contains information on curve characteristics and speed profiles of 153 horizontal curves. In Section 4 we build the Bayesian model, present the results, and run a number of case studies for demonstration purposes. The results are then discussed in Section 5, and in Section 6 the general conclusions of this research and recommendations for future research are drawn.

2. Literature review

2.1. Known variables related to deceleration in curve approach

In general, deceleration modelling studies show that the deceleration in curve approach is correlated to the approaching tangent length, cross section design, horizontal curve radius and deflection angle (Bobermin et al., 2021; Farah et al., 2019; Nama et al., 2020; Sil et al., 2020; Vos and Farah, 2022). The position where drivers start to decelerate is correlated to the speed driven before the curve, visibility of guiding elements such as tree lines or curve signs (i.e. available sight distances), the cross section and number of lanes available, and the horizontal curve radius itself (Vos et al., 2021b). In a survey study by Vos et al. (2021a) drivers indicate that the number of lanes and road type are elements in the road design that influence their speed choice during curve approach besides the presence of signs. And indeed, these elements influence the position where drivers start to decelerate before a curve (Vos et al., 2021b), and have been found to influence speed in the curve itself as well in numerous speed prediction studies (Calvi et al., 2018; Colombaroni et al., 2020; Montella et al., 2024). Furthermore, preceding curves help to recognise the sharpness of an upcoming curve. Sil et al. (2022) show how drivers distinguish between consecutive curves based on the different radii and angles of consecutive curves, and Xu et al. (2022) show how this has more effect if consecutive curves are closer to each other. Driving task analysis research has resulted in descriptions of how drivers anticipate and approach a curve (Campbell et al., 2012; McKnight and Adams, 1970). In these descriptions, roadside signs or the roadway scene which provides evidence of a curve are given as indicators of curves, while during the approach itself drivers are thought to adhere to the posted speed or estimate a safe speed from the deflection angle and superelevation of the curve itself and other features in the environment.

2.2. Curve perception and speed reduction

Both the driving task descriptions, and a recent eye-tracking experiment which captured anticipatory fixations during curve approach (Vos et al., 2023) show that the first cue drivers use is a change in the heading of the roadway. This is thought to be a change in the patterns of visual motion driver perceive as they move – i.e. optic flow – on the point in the visual field where these patterns appear to converge – i.e. the Focus of Expansion (Gibson, 1950). This means drivers see a change in the road direction on the horizon and start decelerating after that. During the 1970 s the road picture of curves as it is perceived by the driver was analysed using perspective drawings with sets of hyperbola (Springer and Huizenga, 1975). From these perspective analysis it is known that this change of direction is seen as a kink, and opens up and reveals curvature when the driver gets closer to the curve. Brummelaar (1975) provides the following equation to calculate the distance at which the curve opens up:

$$Z^2 = R_h(46h - 2a) \quad (1)$$

where:

Z=approach distance at which the curve appears to be open (m).
R_h = horizontal radius of the curve (m).
h = height of the observer's eye (m).
a = distance of the observer to the road edge (m).

So, equation (1) gives quantifiable information about the distance from the observer to curve start (Z) at which the curve is perceived to open and reveal its curvature. This equation only calculates road edges as the perspective drawings only provided road edges, but recent eye-tracking research (Vos et al., 2023) shows that other parallel lines or edges such as tree lines or noise barriers running parallel to the curve are also used by the driver to anticipate that curve. This is in line with Gestalt principles of organisation which show parallel edges to the curve are heuristically used to anticipate the trajectory of a curve (PIARC, 2016). To quantify the effect of parallel edges on curve perception, we assume that the eye-height in equation (1) can also be used to alter the height of the road edge, and thus of a parallel edge. Fig. 1 shows the sight line as intended in equation (1), and the sight line used to calculate the height of a parallel edge. If an eye-height of 1.1 m above the road is used, a parallel edge of 2.2 m above the road results in the same perspective line since it is mirrored at the eye height. Based on this approach, the height of the parallel edge can be used to calculate the distance on which the curve shows curvature. The distance of the driver to the edge has a rather small influence in equation (1). So, if a distance of 5 m from the driver to the parallel edge is set, equation (1) can be used to see what the effects of different heights of parallel edges are on what drivers perceive. This is shown in Fig. 1 using different lines for different heights. Fig. 1 furthermore shows the position where drivers start to decelerate related to the horizontal radius based on an equation derived from analysing speed profiles by Vos and Farah (2022):

$$posBP1 = 155{*}ln(R_h) - 1067 \quad (2)$$

where:

posBP1 = position relative to curve start where drivers start to decelerate (m)
R_h = horizontal radius of the curve (m).

Equation (2) does not consider the existence of a parallel edge, but just estimates the position where drivers start to decelerate in front of a curve generally.

Combining equations (1) and (2) in Fig. 1 shows whether or not the curvature of the curve was visible before drivers started to decelerate. When approaching curves with a horizontal radius of less than 400 m, drivers start decelerating before the road itself shows curvature. A parallel edge which is higher than the road itself could however still show the curvature of the road ahead. For a radius of 300 m, a parallel edge with a height of 3 m would show the curvature to drivers before starting to decelerate, but for a radius of 200 m, a parallel edge of 7.5 m is needed. It is unlikely that parallel edges this high are available. So, particularly for curves with radii of 300 m and less, other cues than the perceivable curvature are thought to be used by drivers to build up the correct expectations on when to start decelerating during curve approach towards an expected safe speed. To know which cues are actually used by drivers, an understanding of the driving task during curve approach is needed.

2.3. Driver expectations

Ranney (1994) positions steering and braking on the operational driving task level. This means that anticipation in curve approach mostly consists of skill-based behaviour that is fully automatised (Rasmussen, 1983) and mostly without awareness (Harms et al., 2019) based on what

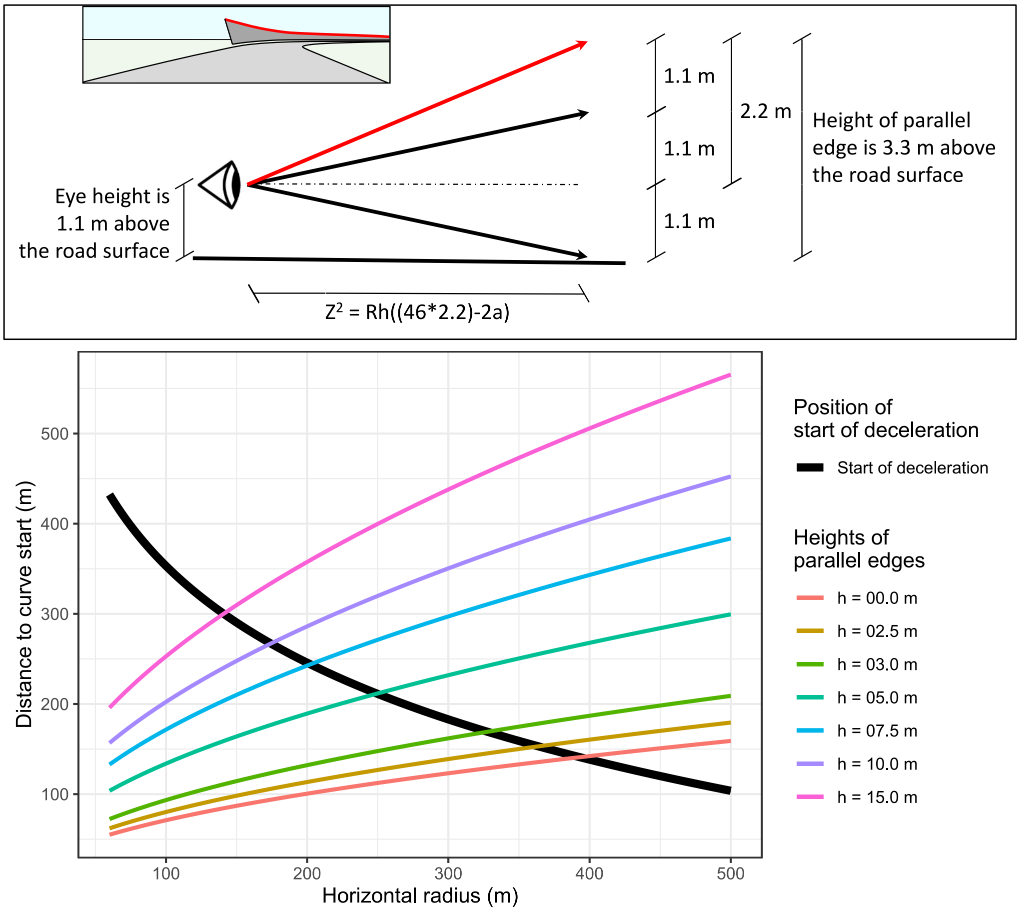

Fig. 1. Analysing the perception of parallel edges in curves regarding their height. The top panel shows how equation (1) is used to calculate from which distance Z a curve shows its curvature to drivers, based on the height of a parallel edge. The red line shows the edge of a noise barrier as an example. Since the eye-height above the road surface can be mirrored we can use the height of the parallel edge minus the eye height to calculate Z. The bottom panel is a diagram showing the effect of different heights of parallel edges on the visibility of curvature and the starting point of deceleration related to the horizontal radius. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

people have learned to expect (Theeuwes et al., 2012). These expectations are based on the development of mental categories, or schemata, containing curve cues and corresponding safe speeds (Charlton and Starkey, 2017b), which are built upon multiple episodes (Ghosh and Gilboa, 2014) and hence relates to the experience of drivers and familiarity with situations. In human information processing models (Wickens et al., 2021), schemata reside in the long term memory (Plant and Stanton, 2013) and therefore act as input for the working memory to select the correct response based on perception as is illustrated in Fig. 2. A schema helps drivers optimize their behaviour and make quick decisions on a safe speed based on cues they perceptually receive and on expectations stored in schemata (Charlton and Starkey, 2017a, 2017b; Ranney, 1994).

2.4. Statistical learning

Expectations are built on regularities in the environment. Since drivers spend much of their driving time on freeways, it can be assumed they have passively learned about regularities in the road environment (Theeuwes, 2021). These regularities are assumed to be extracted from the environment by the drivers to build expectations through statistical learning (Sherman et al., 2020). Statistical learning is thought of as a cognitive mechanism to discover underlying structures and distributions of these perceptual cues and their distributions (Frost et al., 2015) and is known to help build schemata in temporal tasks such as spatial navigation (Graves et al., 2022). Based on these schemata, drivers then come to expect a certain safe speed *given* certain cues.

Research on how cognitive judgments compare with optimal statistical inferences in real-world settings suggests that people adopt expectations in line with the statistics in the real world (Griffiths and Tenenbaum, 2006; Seriès and Seitz, 2013). It has furthermore been found that drivers also learn these regularities and differences for spatial navigation (Chanales et al., 2017; Graves et al., 2022). We therefore assume that drivers also infer a safe speed based on statistical learning of regularities in the road environment (Theeuwes, 2021). Statistical learning is best understood in Bayesian terms of probability (Tenenbaum et al., 2011). This means drivers have a conjecture or belief about a range of safe speeds, which is defined as a probability distribution, given certain curve cues which are available as evidence. Fig. 2 shows how in this research the human information processing is connected to a Bayesian approach by using probability distributions as constructs to resemble a driver's schemata. The next section explains the Bayesian approach, and the connections with human information processing.

2.5. Bayesian approach

In the Bayesian approach each safe speed, v_i, can be associated with a degree of belief $P(v_i)$ from a probabilistic standpoint. This is called a *Prior* belief, and in a freeway curve approach, the *Prior* belief for the safe speed in free flow conditions on a freeway tangent would be around 120 – 130 km/h. Based on experience, drivers are assumed to have learned the *likelihood* of the appearance of different cues, c, given certain safe

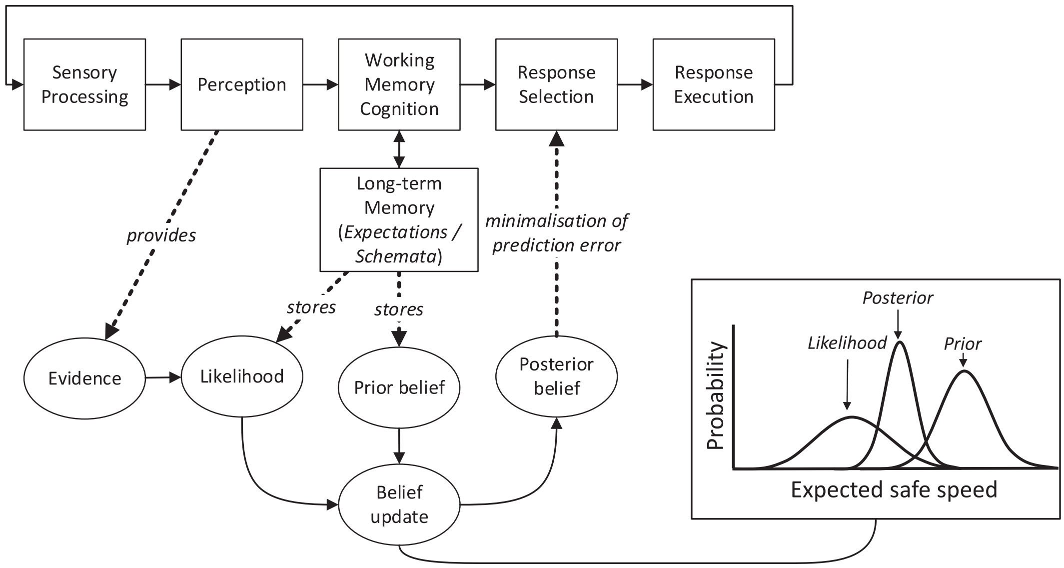

Fig. 2. Human information processing (squares) and Bayesian belief updating (ovals) with assumed connections in dashed arrows. The model of information processing is simplified from Wickens et al. (2021) and includes the notion that schemata reside in long term memory (Plant and Stanton, 2013). This figure shows how the perception of a cue provides evidence in Bayesian modelling. This evidence has a learned likelihood of appearing given certain safe speeds, which are thought to resemble stored expectations (schemata). Using the prior probability of safe speeds, and the likelihood, the belief (expectation) is updated toward a posterior belief upon which the driver is thought to select an appropriate response via prediction error minimisation (Engström et al., 2018). The box connecting the belief update, shows example probability distributions of prior belief on safe speeds, the likelihood of the evidence and the following posterior belief given that evidence.

speeds on this tangent, such as speed signs. Using Bayes theorem, a *Prior* belief about safe speed can be updated based on new evidence – thought to be the perception of a cue –which results in a *Posterior* belief based on the following equation:

$$P(v_i|c) = \frac{P(c|v_i) \bullet P(v_i)}{P(c)} = \frac{P(c|v_i) \bullet P(v_i)}{\sum_i P(v_i) \bullet P(c|v_i)} \quad (3)$$

where:

$P(v_i|c)$ = *Posterior* belief for safe speed given a certain cue
$P(c|v_i)$ = *Likelihood* of a cue appearing given a certain safe speed.
$P(v_i)$ = *Prior* belief for safe speed.
$P(c)$ = *Marginal* probability of a cue appearing.
$\sum_i P(v_i) \bullet P(c|v_i)$ = Sum of (*Prior* * *likelihood*) over all safe speeds.

Equation (3) shows the *Posterior* belief is the conditional probability of a safe speed given a certain visual cue denoted as $P(v_i|c)$. It is furthermore known that $P(c|v_i)*P(v_i) = P(c, v_i)$ which is the joint probability for a cue appearing together with a certain safe speed. This type of inference is also referred to as belief updating (Feldman, 2013), because new cues are assumed to lead drivers' belief to evolve from a *Prior* belief to a certain *Posterior* belief – or expectation – of the safe speed in a curve. In this way, the belief about the safe speed, is gradually updated by the cues towards a suitable safe speed for an upcoming curve. Fig. 2 illustrates how likelihoods and beliefs are assumed to be stored in schemata and hence resemble expectations. Thus, *beliefs* in Bayesian terminology are translated to *expectations* in driver information processing models. Using Bayesian statistics is hence not an additional statistical model to estimate speeds, but a method to understand how drivers build expectations.

Since several cues might indicate an upcoming curve, it is suitable to develop a Bayesian belief network (BBN), since these are able to model conditional dependence between the cues (Pearl, 1988). Such networks are acyclic directed graphs in which nodes represent the random variables and connections represent the direct probabilistic dependence among them. In general, the direction of influence in a Bayesian belief network 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 particular state. The conditional probability distributions are captured in conditional probability tables (CPT's) which describe the likelihood of a particular node's state, given the state of its parent nodes. Belief updating in a BBN is induced by observing evidence. A node (cue) that has been observed is called evidence, and by observing the evidence, the probability distribution is updated towards a certainty and gets propagated through the network, modifying the probability distribution of other nodes (cues and expected safe speed). In this way, expectations about safe speeds can be statistically modelled as posterior beliefs of safe speeds, based on observed evidence of curve cues. This process is shown in Fig. 3, where drivers starts off with an approaching speed and updates their expectations of the upcoming safe speed (posterior belief) with each cue received (evidence). Based on this updated belief, the driver is assumed to adjust the operating speed, whenever this does not match the belief of the upcoming safe speed. This process is known as prediction error minimisation (Engström et al., 2018) as shown in Fig. 2. In this process the driver resolves the difference in the belief about the upcoming expected safe speed and the actual operating speed (i.e. prediction error) by deceleration to minimize the risk of skidding in the

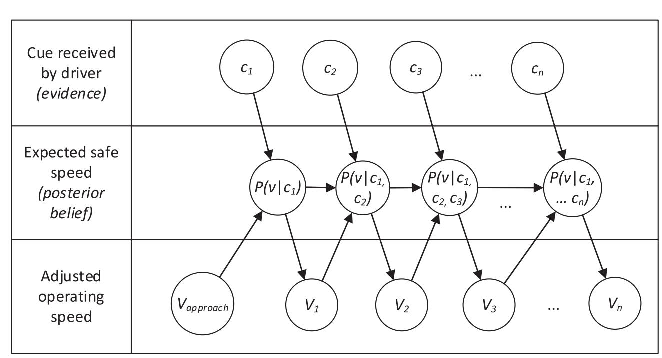

Fig. 3. The process of updating the expected safe speed in a curve given the received cues (C_1, C_2, C_3, …, C_n) and adjusting the operating speed accordingly.

Table 1
Distribution of cues in the available database.

Cue	N	%	Cue	N	%
Turning direction			***Speed sign present***		
- Left turning	48	31 %	- Advice speed 50 km/h	10	7 %
- Right turning	105	69 %	- Advice speed 60 km/h	8	5 %
Preceding roadway			- Advice speed 70 km/h	9	6 %
- Main carriageway	43	28 %	- Advice speed 80 km/h	3	2 %
- Connector road	50	33 %	- Advice speed 90 km/h	8	5 %
- Deceleration lane	21	14 %	- Speed limit 50 km/h	5	3 %
- Fork	13	8 %	- Speed limit 60 km/h	1	1 %
- Weaving section	24	16 %	- Speed limit 70 km/h	12	8 %
- Merge	2	1 %	- Speed limit 80 km/h	4	3 %
Speed in preceding curve			- Speed limit 90 km/h	2	1 %
- 60 – < 80 km/h	2	1 %	- No speed signs present	91	59 %
- 80 – < 100 km/h	13	8 %	***Curve warning sign present***		
- 100 – < 120 km/h	26	17 %	- Curve warning sign present	49	32 %
- 120 – < 140 km/h	11	7 %	- No curve warning sign present	104	68 %
- Preceded by tangent	101	66 %	***Curve chevron signs present***		
Number of lanes in curve			- Curve chevron signs present	48	31 %
- One	76	50 %	- No curve chevron signs present	105	69 %
- Two	58	38 %			
- Three	15	10 %			
- Four	4	3 %			
Deflection angle of curve					
- 10 – < 100 grad	82	54 %			
- 100 – < 200 grad	50	33 %			
- 200 – < 310 grad	21	14 %			

curve (Wilde, 1998) or feelings of discomfort (Summala, 2007).

3. Methods

3.1. Data collection and analysis

The database generated by Vos et al. (2021b) is used in this research to model prior beliefs about expected safe speeds and the likelihoods of cues (evidence) appearing given certain expected safe speeds. Each of the 153 curves in the database has detailed information about its geometry and surroundings and is accompanied by about one million unique free-flow speed profiles taken from High Frequency Floating Car Data (HF-FCD) from a smart-phone navigation app called “Flitsmeister”. The data was collected in the Netherlands, during March, April and September 2020. No alterations to the infrastructure were made during that period. Detector loop data was used to identify instances of free-flow traffic (i.e. headways exceeding 5 s). Only the HF-FCD from these periods was used in the analysis. This dataset is assumed to reflect different schemata in which expectations are stored in the driver’s memory, since schemata on safe speeds are built in the driver’s memory based on multiple experiences (Charlton and Starkey, 2017b). For different curve cues the database contains measured speeds, reflecting the cues drivers perceive and the response (i.e., decelerating) the drivers adhered to. Table 1 shows how the available cues are distributed among the curves in the database. Speeds in preceding curves and the angles of the curves were discretised into intervals of respectively 20 km/h and 100 gradients. The speeds were grouped into 20 km/h because this ensures that each interval has enough data points to use in the model and generate reliable marginal probabilities (e.g. to prevent having intervals without data points). The variable “preceded by tangent” was added to reflect tangents or large radii which do not impact the approach speed of a curve. Since freeways in the Netherlands have divided carriageways, the number of lanes is given for the carriageway the curve is positioned in. Deflection angle was grouped in three categories that would be easily distinguishable by drivers (e.g. straight corners) since exact angles are hard to perceive from a distance (Riemersma, 1988), but direction (left or right) is. For each of the collected free-flow speed profiles, we calculated the speed which the driver adhered to in the curve. Since a single speed profile consists of a string of speed measurements with a frequency of 1 Hz, we assume that the mode of the measured speeds in the curve is the speed the driver deemed safe, since this is the speed the driver drove the longest inside the curve. For each of the curves, we then establish an 85th percentile of the modal speeds driven in those curves. In transportation research, the 85th percentile speeds are frequently employed. The selection of a specific quantile is not critical as the various percentiles exhibit similar patterns in the speed profile. The correlation between median speeds and the 85th percentile speeds in the data is remarkably robust and statistically significant, with a correlation coefficient of 0.98 ($t = 789.84$, $p < 0.001$). This underscores the limited sensitivity when using alternative quantiles, because the probability distributions will have the same distribution, but with lower speeds when using median speeds.

The 85th percentile of the measured median speeds in curves have been used as the independent variable for generating the probability distributions of the cues represented in Table 1. This gives the first probabilistic view on the expected safe speed for different curve cues independently.

3.2. Modelling a Bayesian belief network

The modelling and analysis was done in the GeNIe Modeler (GeNIe Modeler (Version 4.0.R2), 2022), which is an interface to the Structural Modeling, Inference, and Learning Engine (SMILE) (Druzdzel, 1999). The interface allows to use the dataset to learn and evaluate the Bayesian belief networks (BBN). To model the variables in a BBN, we discretised the speeds into intervals since speed cannot be modelled as a continuous variable, as these do not have a linear distribution. We iterated the interval-size, and an interval-size of 10 km/h was found most appropriate: smaller intervals gave intervals without enough data-points, larger intervals showed less detail. We started by building and analysing a naïve Bayesian network (NBN), shown in Fig. 4. A NBN assumes all variables to be independent, so using a NBN we can independently test the strength of influence of each variable on the class label, which in this case is the safe speed. The class label expected safe speed is the *prior* belief, which can be updated by observed evidence of cues and calculate the *posterior* belief of the expected safe speed given the observed evidence using equation (3). The strength of influence is measured using the average Euclidian distance between the expected safe speed and the cues (Koiter, 2006) and therefore refers to the degree to which the probability of a particular variable is influenced by another variable.

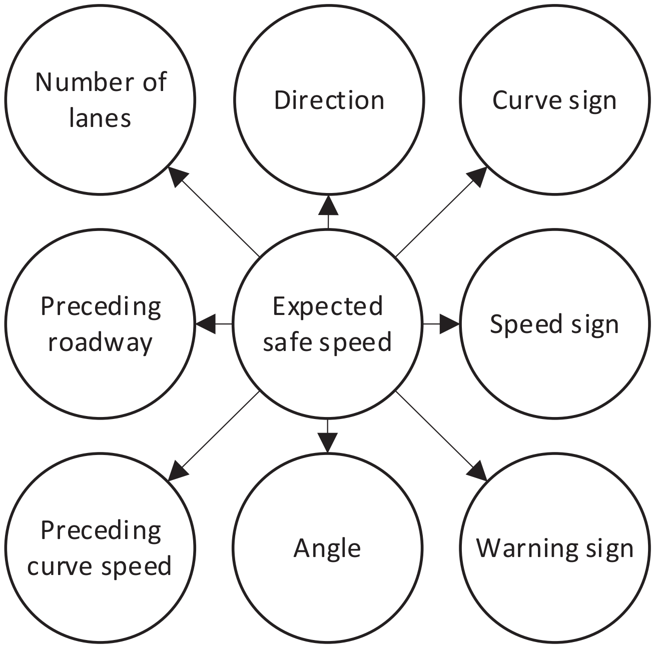

Fig. 4. The naive Bayesian network (NBN).

However, different cues might be interdependent of each other. For example, the co-occurrence of particular signs or the tendency for forks to have more lanes than deceleration lanes. So, an NBN probably does not reflect how driver expectations are constructed, because these interdependencies are assumed to be learned by the driver as well, as these cues tend to be observed together. To investigate the interdependence of the variables we have learned a Tree Augmented Naïve Bayes (TAN) structure using the interdependencies in our dataset. The TAN algorithm uses the NBN structure and adds connections between the different cues to account for dependence, conditional on the expected safe speed (Friedman et al., 1997). The TAN algorithm allows for one extra connection between cues to be added based on the highest amount of mutual information regarding the expected safe speed in the extra connections.

3.3. Testing and validating

The learning and testing of the networks is done via an expectation maximization (EM) algorithm which selects random values for parameters to learn the optimal values. A higher log-likelihood indicates a better fit of the model to the data. Validating the TAN is done by using a Leave One Out (LOO) procedure to test how well the network performs when one record is left out in the learned data and see how well the TAN predicts the expected safe speed for that left out curve. Furthermore, the TAN is validated in two empirical case studies in which visual cues are compared with actual speed profiles and the outcomes of the TAN for the shown cues. Following that, various hypothetical cases are presented, altering one variable at a time to observe the TAN's response. Lastly, the TAN's validation includes assessing the sensitivity of several variables in the dataset concerning their discretisation or interdependence.

4. Results

The following sub-sections describe the results of the data analysis and modelling. Subsection 4.1 starts with the probability distributions of individual cues, subsection 4.2 models these cues into Bayesian Belief Networks (BBNs). These BBNs are tested and validated in section 4.3, and section 4.4 shows the use of a BBN in several case studies.

4.1. Probability distributions of curve cues

For each available cue, the probability distribution of the measured 85th percentile median speeds is plotted. These are given in Fig. 5 and can be interpreted as naïve *Prior* beliefs, so as independent variables.

Fig. 5 shows how the measured speeds are distributed along different cues. Several cues show clear differences in the speed distributions. For example, a 50 km/h speed sign or a large angle are associated with low speeds, while a presence of 4 lanes would be associated with larger speeds (i.e., no need to decelerate).

4.2. Bayesian belief networks

The NBN in Fig. 4 had its parameters learned based on the observed data in the dataset. This resulted in an EM Log Likelihood of −1286.58 and the strengths of influences given in Table 2. The average strength of influence in Table 2 show a large value of the angle on the expected safe speed, followed by the type of preceding roadway, presence of curve and speed signs as well as the number of lanes. Other cues, such as warning sign, preceding curve speed, and curve direction showed less strength of influence.

Next, a tree augmented naïve Bayesian network (TAN) was learned based on our data using expected safe speed as the class label. This resulted in an EM Log Likelihood of −1026.19. Other learning algorithms (i.e. "Bayesian Search", "PC", "Greedy Thick Thinning") led to lower EM Log Likelihoods. The learned TAN is given in Fig. 6 and the average strength of influences per connection are given in Table 3.

Since the type of preceding roadway influences the number of lanes greatly, the number of lanes has a larger strength of influence on the safe speed in the TAN than in the NBN. Furthermore, the interdependence among the variables, leads to a lower influence of speed signs in the TAN. The conditional probability tables (CPTs) for the TAN are given in Appendix A.

4.3. Validation

The learned TAN shown in Fig. 6 underwent validation through three distinct methods, namely cross-validation, case studies, and sensitivity analysis. These approaches will be elaborated upon in the following sections.

4.3.1. Cross-validation

We cross-validated the TAN using a Leave One Out (LOO) procedure using our dataset, meaning the TAN structure was trained 153 times, each time leaving one case out and predicting its expected safe speed on the trained TAN of 152 cases. Overall, the class variable – expected safe speed – was predicted correctly (i.e., within the same interval as the measured 85th percentile median speed) 51 % overall, and for 82 % within an average of 10 km/h offset (i.e., adjacent interval). The confusion matrix is shown in Table 4, showing the variability around the correct predictions for most expected safe speeds is better predicted in the lower speeds than in the higher speeds.

4.3.2. Case studies

The cross-validation in the previous section was done using all observable evidence upstream of the curve (cues) to predict an expected safe speed inside the curve. The assumption, however, is that drivers update their expectations about a safe speed during curve approach using cues as they appear during curve approach as illustrated in Fig. 3. The temporal process of belief updating during curve approach is tested in two case studies, and is another way of validation of the TAN because it is tested in untrained conditions – i.e. the TAN was trained using all available cues of a curve simultaneously, while during curve approach cues become visible separately. We present two curve approaches providing the measured speed profiles using the data from Vos et al. (2021b) and the available cues to the driver in four pictures along the

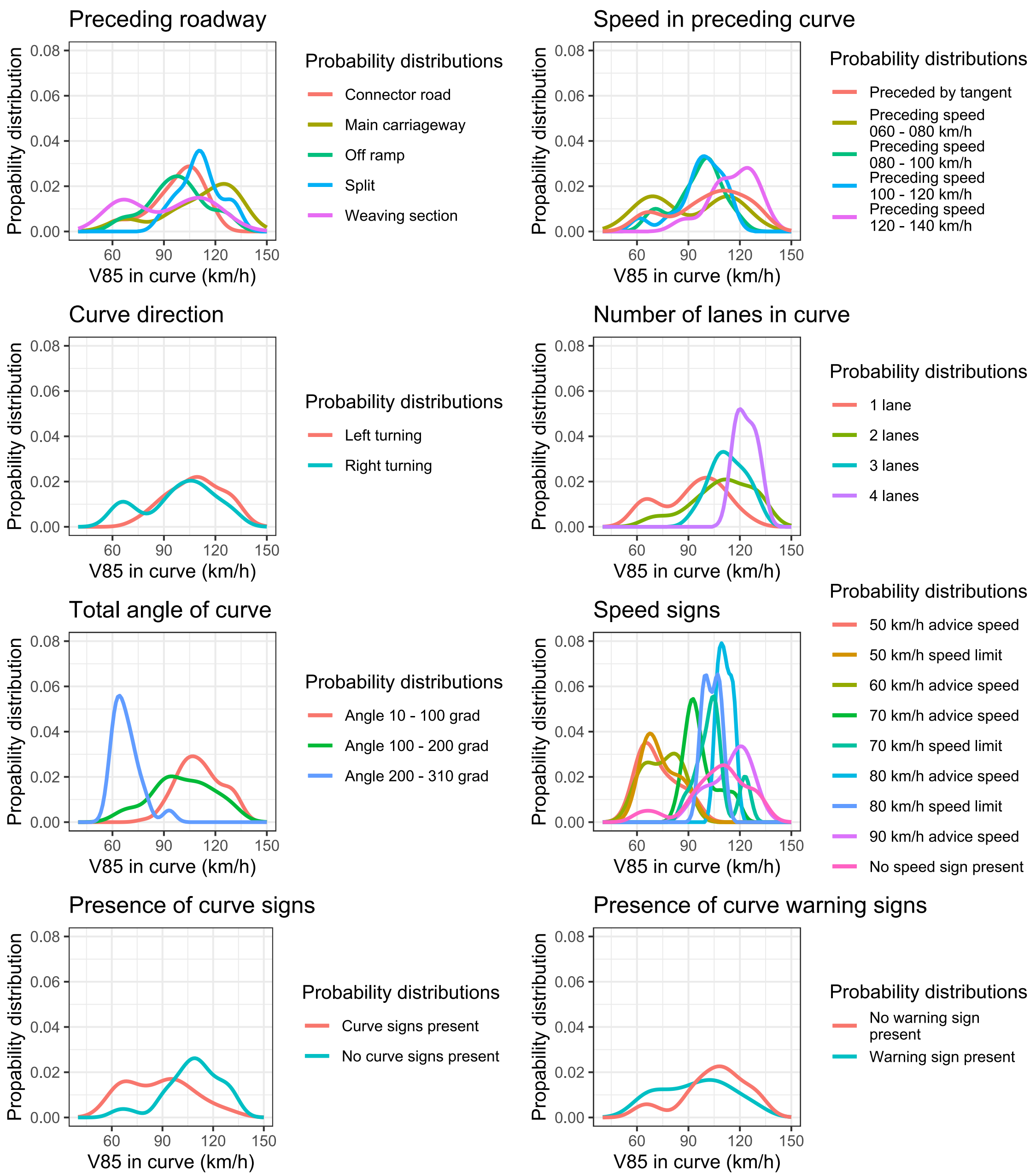

Fig. 5. Probability distributions for the eight different variables (cues) related to the 85th percentile measured median speeds in a curve.

Table 2
Average strength of influence for each connection in NBN.

Parent	Child	Average strength of influence
Expected safe speed	Angle	0.4403
	Preceding Roadway	0.3470
	Curve sign	0.3181
	Speed sign	0.3096
	Number of lanes	0.3073
	Warning sign	0.2074
	Preceding curve speed	0.1792
	Direction	0.1783

approach. These cues are then set as evidence in our TAN, to see how the resulting expected safe speeds (i.e., *posterior* belief about safe speed) resembles the speed development in the actual speed profiles. The TAN is shown in Fig. 7 without observed evidence, i.e. no visible cues.

The case studies show which evidence was set in the TAN by underlining a specific definition of a node and setting its probability to 100 %. The expected safe speed is shown in the case studies as a probability distribution in red, using the distributions in the expected safe speed intervals.

Case study 1 starts in picture B in Fig. 8 with a connector road visible with two lanes in a curve in which the 85th percentile of the operating speeds is between 100 and 120 km/h, no signs are visible, and no curve angle or direction can be estimated of the upcoming curve. The expected safe speed is between 80 and 120 km/h. Then in picture C it becomes clear the connector road continues in one lane, the expected safe speed drops to 60 to 120 km/h, which corresponds to a speed drop in the 15th percentile speeds. Then the curve and its angle become visible in picture D, which narrows the expected safe speed towards the lower speeds and leads to a decrease in the 85th percentile operating speed. After seeing the advisory speed of 60 km/h, together with warning and curve signs before entering the curve in picture E, the expected safe speed shifts drastically to a range between 60 and 70 km/h, and from that moment

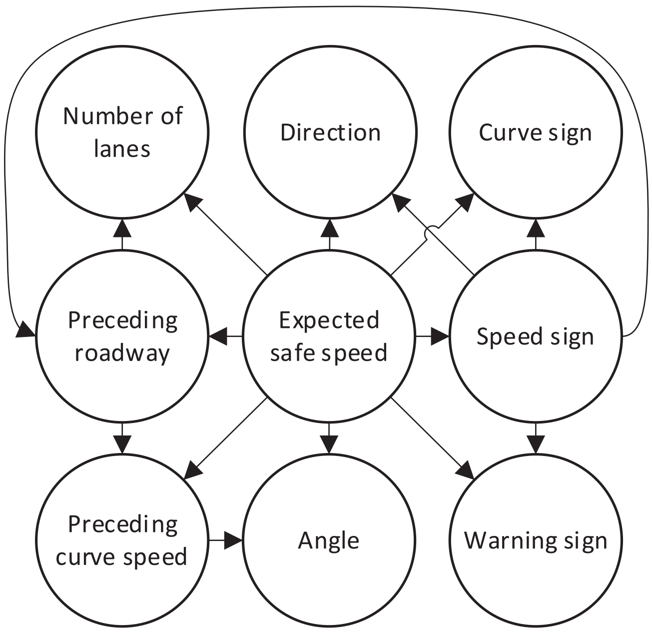

Fig. 6. The tree augmented naive Bayesian network (TAN), learned from the data with the expected safe speed set as the class variable.

Table 3
Average strength of influence for each connection in the learned TAN.

Parent	Child	Average strength of influence
Preceding roadway type	Number of lanes	0.4458
Expected safe speed	Angle	0.4235
	Number of lanes	0.3832
Preceding roadway type	Preceding curve speed	0.3706
Preceding curve speed	Angle	0.3564
Expected safe speed	Speed sign	0.3192
	Preceding roadway type	0.2907
Speed sign	Preceding roadway type	0.2818
Expected safe speed	Preceding curve speed	0.2764
Speed sign	Warning sign	0.2500
	Curve sign	0.2304
	Direction	0.2083
Expected safe speed	Curve sign	0.1971
	Direction	0.1865
	Warning sign	0.1796

also the 15th percentile operating speeds starts to drop. Case study 2 starts in picture B with one lane on a fork – the right side of the block markings. The expected safe speed in an upcoming curve is predicted between 80 and 120 km/h, but since the drivers drive on a tangent, the operating speed is relatively high, and then gradually lowered. Picture C shows how the carriageway leading to the curve actually has two lanes instead of the one lane on the preceding fork, so the expected safe speed gets updated to a higher speed range, between 100 and 140 km/h. A small increase in 15th percentile operating speeds is noticed here. Next, the curve direction and angle become visible in picture D, this creates a little difference in the probability distribution of the expected safe speed. From this position onwards the measured operating speed starts to drop. Once the speed and warning signs in picture E become visible, the expected safe speed is updated to the range of 100 to 110 km/h, in line with the 85th percentile operating speeds in the curve. See (Fig. 9).

Several hypothetical cases were tested in the TAN. The results are given in Table 5 (and visually presented in Appendix B). Table 5 shows how changing different elements in the design could change the expectations of drivers about a safe speed, as the column of expected safe speeds show the expected safe speeds with the highest probability. Appendix B shows the different variabilities of expected safe speeds visually as resulting probability distributions.

4.3.3. *Sensitivity analysis*

Because the variables “preceding curve speed”, “angle”, and “expected safe speed” were discretised, we did a sensitivity analysis on the intervals. First, we constructed a database including intervals of 10 km/h for the speed in preceding curves speed and intervals of 50 gradients for the deflection angle Training a Tree Augmented Naive Bayes (TAN) on this database resulted in an EM Log Likelihood of −1087, indicating a poorer fit to the data compared to the previously presented TAN. Next, we generated another database using 5 km/h intervals for the median speed inside the curve and trained a TAN on it. The resulting EM Log Likelihood was −1030, which is nearly identical to the presented TAN. However, this model exhibited more instances of 0 % probability between predicted speeds where the probability was higher than 0 %. This suggests a less accurate representation of expectations, as multimodal probability distributions may imply indecision or conflicting thoughts among drivers. Such occurrences are unusual due to the subconscious nature of speed adaptation.

The interdependence of specific signs to speed differences is covered in Dutch guidelines for traffic control devices, based on the k-value for speed differences between upstream of the curve and inside the curve (Richtlijnen voor de bebakening en markering van wegen, 2015). This suggests that these signs alone should be a good predictor of the safe speed. To test this, a TAN was learned using only the preceding curve speed, speed signs, warning signs and curve signs as nodes. The validation of this TAN using the LOO-procedure shows that the TAN only has a correct prediction of the safe speed in 38 % of the cases. This is lower than the 51 % in the TAN presented in Fig. 6, which shows the influence of other variables, shown in Table 3, together with signs is relevant to build expectations.

Table 4
Confusion matrix for cross validating the expected safe speed in the tree augmented naïve Bayesian network with the measured 85th percentile median speeds.

		Predicted expected safe speed (km/h)							
		60 – 69	70 – 79	80 – 89	90 – 99	100 – 109	110 – 119	120 – 129	130 – 140
Measured 85th percentile median speeds (km/h)	60 – 69	**14**	3	0	0	0	0	0	0
	70 – 79	2	**5**	2	0	0	0	0	0
	80 – 89	0	0	**7**	2	1	0	0	0
	90 – 99	1	0	1	**17**	5	1	1	0
	100 – 109	0	0	0	7	**16**	6	5	0
	110 – 119	0	0	0	6	9	**8**	3	2
	120 – 129	0	0	0	3	3	3	**6**	2
	130 – 140	0	0	0	0	0	4	2	**6**

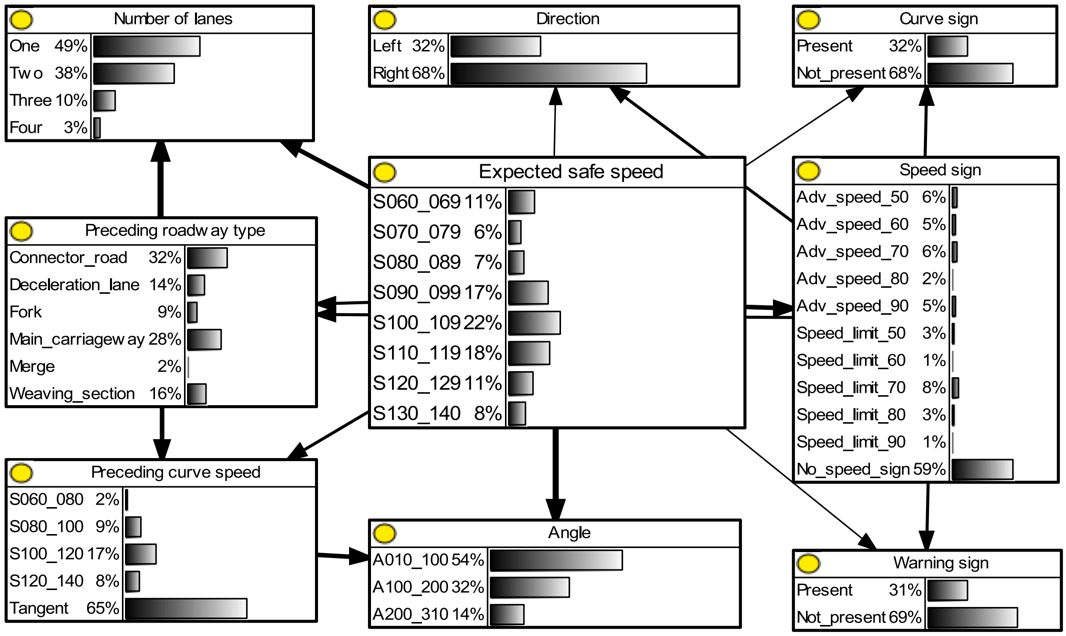

Fig. 7. The tree augmented naive Bayesian network with bar charts in each node showing the probabilities for each possible definition of that node, without having any evidence set. The thickness of each connection (arrow) indicates its strength of influence.

5. Discussion

Since Bayesian statistics are thought to resemble how drivers build their expectations, this approach can be used to model speed behaviour in curve approach. These results can then be used pro-actively in assessing the safety of a road design. This research starts by analysing the measured 85th percentile speed probability distributions in a curve dependent on the individual cues during curve approach. Several cues have a zero probability for certain speeds. These include speed signs, high number of lanes, forks, high preceding speeds and large curve angles. When these cues are present, they reduce the probability of certain speeds (e.g., low speeds for high number of lanes and high speeds for large curve angles) to zero. These variables also tend to have a higher strength of influence in the explored Bayesian Belief Networks (BBNs). The deflection angle of the curve has a strong influence on the expected safe speed in the curve, which is in line with the notion that increasing angles are associated by drivers with tighter curve radii (Riemersma, 1988) and that the visible angle of the curve is related to how drivers assess their expected safe speed in curves (Vos et al., 2021a). The total angle of a curve might however be – partially – obscured. The visible angle, which drivers are also assumed to derive from parallel edges, can hence only be used as evidence during curve approach when completely visible to the driver, calling for large sight distances. The preceding roadway and the number of lanes are however clearly visible upon curve approach, and, when these cues are analysed interdependently in a Tree Augmented Naïve Bayes (TAN) structure, the preceding roadway and number of lanes show a strong influence on the expected safe speed. In case studies, where the TAN was applied in a temporal order along a curve approach, the updated expected safe speeds for the upcoming curve follows the actual measured operating speed profile, validating how this TAN indeed mimics the curve approach behaviour by minimising the prediction error through deceleration. Both the strength of influence of the speed signs in the TAN, as well as the case studies show a low influence of speed signs, even though the probability distributions of speed signs show that measured 85th percentile speeds which deviate much from the (advisory) speed limit have low probabilities and are hence thought to have a large influence. This could be the result of a high interdependency between the speed signs and the measures speeds and underpins the findings by Vos et al. (2023) who showed that speed signs are mostly used by drivers for confirmation for the need to decelerate and not as an independent cue.

The cross-validation of the TAN shows that it is better suited for predicting relatively low expected safe speeds, as the confusion matrix shows more off-target predictions when the speeds get higher. This is in line with the identified need for additional cues than perceivable curvature when approaching smaller radii, since these are hard to perceive. Better predictability of curves which have low operating speeds suggest a more uniform curve approach – at least in this dataset – and therefore a better self-explainability.

Finally, we mention some limitations. First, the database we have used was not specifically designed for conducting this research. The relative low number of curves and the high number of variables and conditional probabilities led to several conditional probabilities which are skewed to one or two available records, and hence do not reflect the conditional probabilities of a cue. This is especially present for variables which only have two data points, such as merges or 60 km/h speed limits. However, BBNs are known to perform well with missing data, because they develop probabilities for the missing data (Chen and Pollino, 2012), reflecting low likelihood of appearing. Still, a larger set of curves would give better insights into the conditional probabilities, furthermore the conditional probability tables could be adjusted based on expert knowledge. Also, driver experience and familiarity are not present in the database, which makes it impossible to analyse in depth which schema are learned by drivers. However, Vos et al. (2023) show that familiarity of curves has no influence on the position of deceleration, but does influence the type of fixations. This suggests that familiarity of curves steers fixations (and perception), but not the reaction, which is in line with the automatization of curve approach behaviour.

In addition, the dataset used to model expected safe speeds was based only on data collected in the Netherlands (Vos et al., 2021b). This means that the results only represent expectations about Dutch freeways. The methodology presented in this research, using a Bayesian approach to modelling safe speed expectations, is universally employable whenever enough data or expert knowledge is available on local

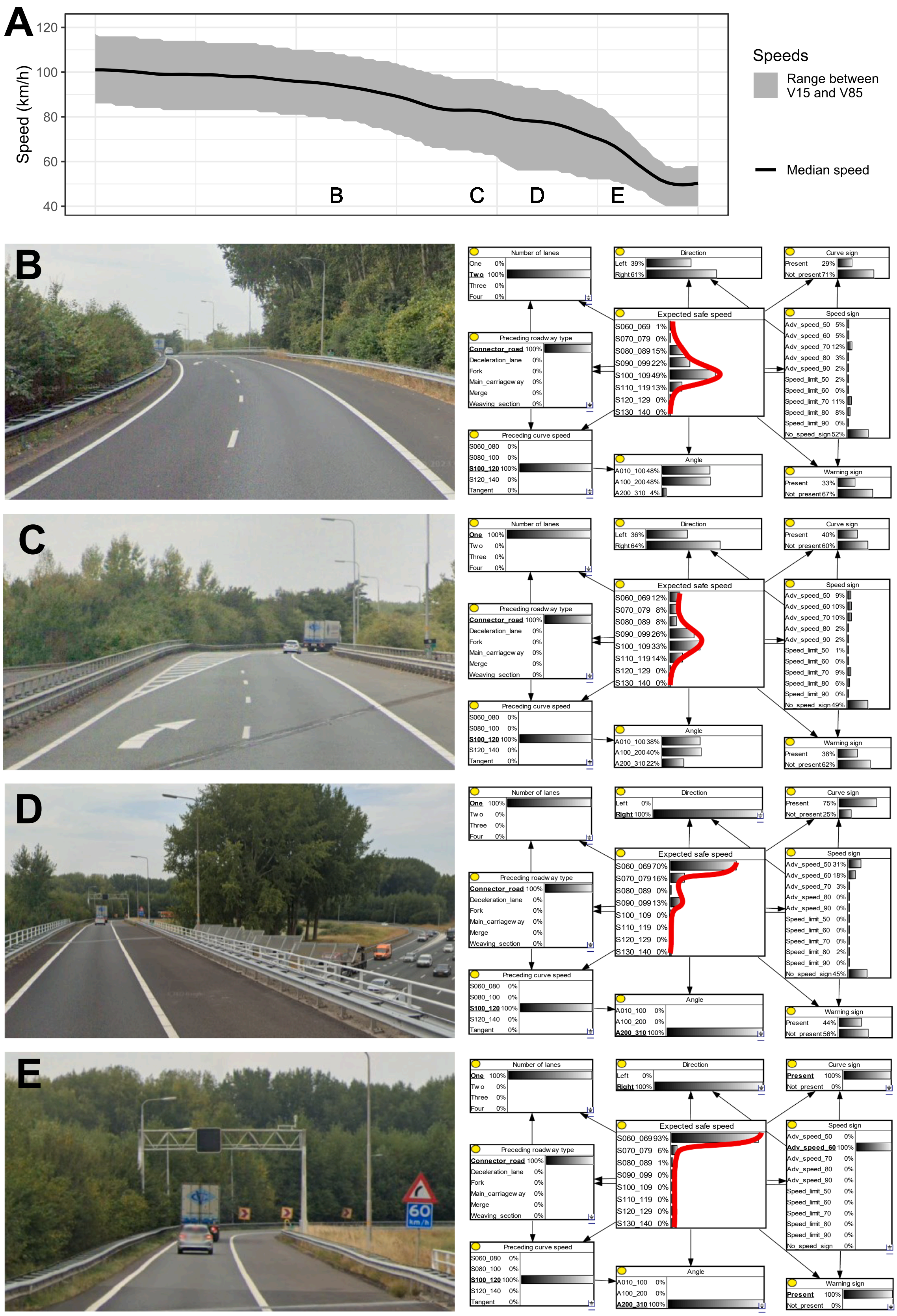

Fig. 8. Case study 1 of belief updating upon curve approach. Panel A shows the measured operating speeds in this curve approach and the positions of the pictures. The pictures in panels B through E show the curve approach with the TAN next to it, updated with the visible cues and the resulting expected safe speed.

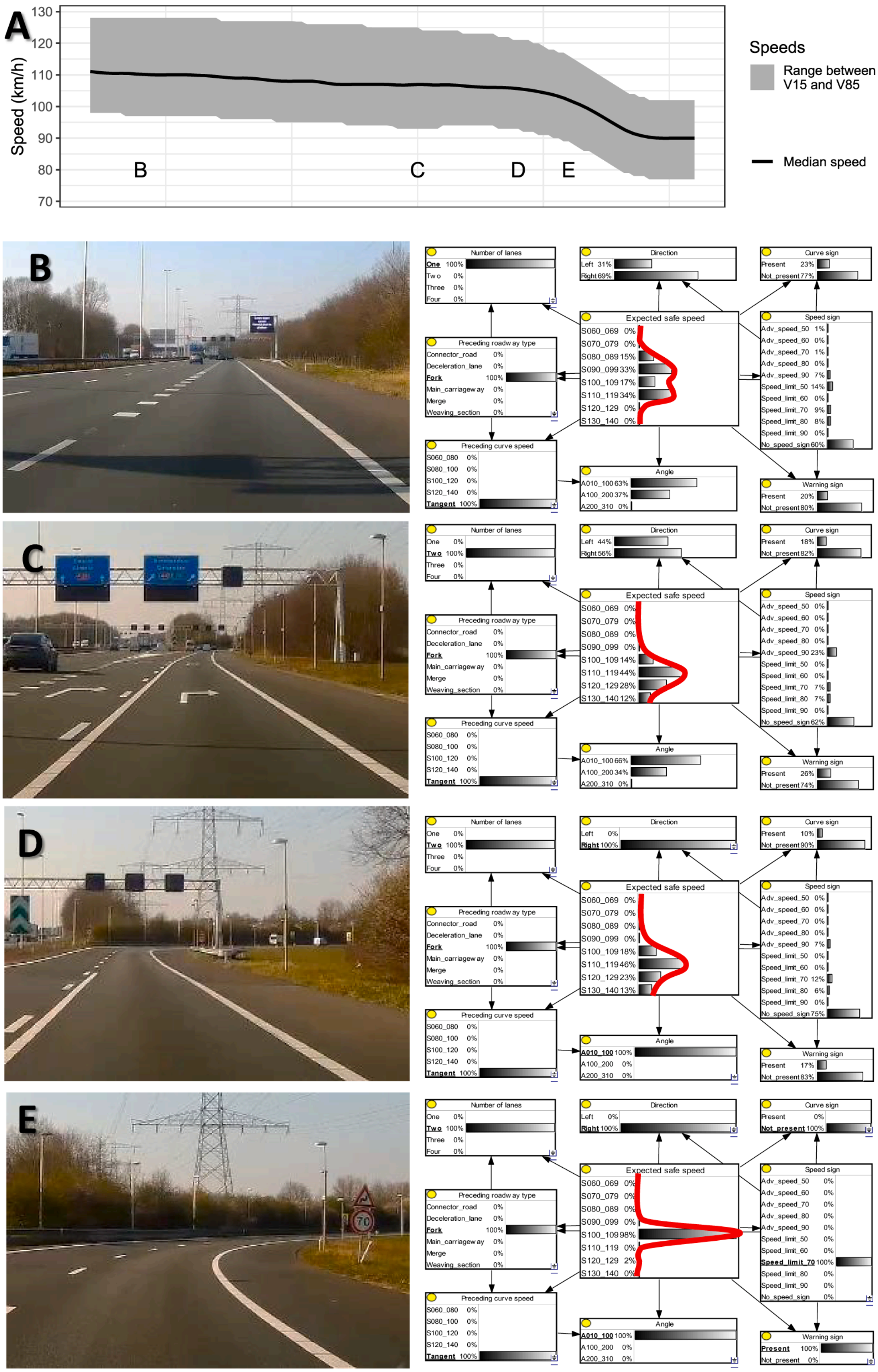

Fig. 9. Case study 2 of belief updating upon curve approach. Panel A shows the measured operating speeds in this curve approach and the positions of the pictures. The pictures in panels B through E show the curve approach with the TAN next to it, updated with the visible cues and the resulting expected safe speed.

Table 5
Expected safe speeds based on different definitions of the nodes in the tree augmented naive Bayesian network (visualisation of the respective TAN's are given in Appendix B).

<table>
<tr><th># in appendix B</th><th>Preceding roadway type</th><th>Preceding curve speed</th><th>Direction</th><th>Number of lanes</th><th>Angle</th><th>Curve sign</th><th>Warning sign</th><th>Speed sign</th><th>Expected safe speed</th></tr>
<tr><td>A</td><td rowspan="2">Main carriageway</td><td rowspan="8">Tangent</td><td rowspan="8">Right</td><td>One</td><td rowspan="9">Not visible</td><td rowspan="6">Not present</td><td rowspan="7">Not present</td><td rowspan="7">Not present</td><td>120–129 km/h</td></tr>
<tr><td>B</td><td>Two</td><td>130–140 km/h</td></tr>
<tr><td>C</td><td>Deceleration lane</td><td rowspan="3">One</td><td>90–99 km/h</td></tr>
<tr><td>D</td><td>Fork</td><td>90–99 km/h</td></tr>
<tr><td>E</td><td rowspan="4">Weaving section</td><td>70–79 km/h</td></tr>
<tr><td>F</td><td>Two</td><td>120–129 km/h</td></tr>
<tr><td>G</td><td>One</td><td rowspan="2">Present</td><td>60–69 km/h</td></tr>
<tr><td>H</td><td>Two</td><td>Present</td><td>90 km/h advice</td><td>110–119 km/h</td></tr>
<tr><td>I</td><td rowspan="2">Connector road</td><td rowspan="2">100 – 120 km/h</td><td rowspan="2">Left</td><td rowspan="4">One</td><td rowspan="2">Not present</td><td rowspan="2">Not present</td><td rowspan="2">Not present</td><td>100 – 109 km/h</td></tr>
<tr><td>J</td><td rowspan="2">10 – 100 grad</td><td>110 – 119 km/h</td></tr>
<tr><td>K</td><td rowspan="2">Deceleration lane</td><td rowspan="2">Tangent</td><td rowspan="2">Right</td><td rowspan="2">Not visible</td><td rowspan="2">Not visible</td><td rowspan="2">Not sighted</td><td>100 – 109 km/h</td></tr>
<tr><td>L</td><td>200 – 310 grad</td><td>60 – 69 km/h</td></tr>
</table>

curve characteristics and driving speeds. Data used to build (local) speed prediction models can also be used in tools like "GeNIe Modeler (Version 4.0.R2), 2022) to easily learn a location-specific TAN using the location-specific cues in the available databases. It might however be needed to change the continuous variables (like speed) into ordinal variables – e.g. using intervals.

6. Conclusions

Estimating curve radii from a distance, which is needed to properly decelerate, is difficult for drivers, especially for smaller radii. Therefore, other cues are needed to assist drivers to build correct expectations about a safe speed. By modelling the expected safe speed in an upcoming curve, dependent on cues during curve approach in a Bayesian Belief Network, we mimic driver's expectations and curve speed approach behaviour. The results show that the preceding type of roadway, and the number of lanes, have a strong influence on the expectations of the safe speed in an upcoming curve. But not as much influence as the deflection angle of the curve, which, when visible using the roadway itself or parallel edges such as tree lines, tells a lot about the range of safe speeds to be expected. Speed signs on the contrary, seem to have a more confirmatory use for the driver. The model can reflect the updating of expected safe speeds in a temporal way during curve approach, resembling operating speed profiles. We conclude that the Bayesian approach to driver behaviour is a useful method in quantifiably modelling driver behaviour. It can be used to pro-actively assess road safety, based on infrastructural elements, since it helps to understand how drivers build and use their expectations about a safe speed. Using the model in a Dutch context, designers and safety auditors can check if a combination of design elements preceding a curve, leads the driver to build a correct expectation about the speed that can be safely driven through a curve. If this expected safe speed does not reflect a design speed for an upcoming curve, the expectations of the driver might deviate too much from the actual curvature and might result in a too high speed during the curve approach. This would then increase accident risks because of speed differences among drivers or potential skidding. Dutch design guidelines can be updated using such insights and relate curve design to the cues the drivers are given when the approach a curve. This would make the design process encompass not just only horizontal radius but also upstream elements, and hence and driver oriented. Because operational speeds are highly correlated to horizontal radii (Farah et al., 2019; Vos and Farah, 2022), this translates into specific horizontal radii being linked to a certain set of design elements upstream and inside the curve (e.g. preceding roadway, number of lanes, deflection angle and signs). Because the cross-validation in Table 4 showed better fit for lower speeds, these combinations of design elements are stricter for smaller radii than for larger radii. In order to use the model in a non-Dutch context, the Conditional Probability Tables need to be revised using local expert knowledge or data on local curve characteristics and driving speeds.

CRediT authorship contribution statement

Johan Vos: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Resources, Validation, Visualization, Writing – original draft, Writing – review & editing. **Haneen Farah:** Methodology, Supervision, Writing – review & editing. **Marjan Hagenzieker:** Conceptualization, Methodology, Supervision, Writing – review & editing.

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.

Data availability

The data used to learn the Bayesian Belief Network is shared on the 4TU.ResearchData Repository via this link: https://doi.org/10.4121/a59fcc0f-4603-490a-b0b8-8b2287141e30. An interactive version of the learned Bayesian Belief Network is shared on the BayesFusion Interactive Model Repository and can be found via this link: https://repo.bayesfusion.com/network/permalink?net=Small+BNs%2FDriver%27s+Expectation.xdsl.

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Appendix A. – Conditional probability tables

Table 6
CPT of node "number of lanes".

Number of lanes	Preceding roadway: connector road							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
One	0.850	0.988	0.499	0.700	0.529	0.444	0.906	0.250
Two	0.033	0.004	0.499	0.300	0.412	0.222	0.031	0.250
Three	0.061	0.004	0.001	0.000	0.059	0.333	0.031	0.250
Four	0.056	0.004	0.001	0.000	0.000	0.000	0.031	0.250
Number of lanes	Preceding roadway: main carriageway							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
One	0.498	0.009	0.250	0.001	0.200	0.125	0.250	0.000
Two	0.498	0.972	0.250	0.797	0.399	0.749	0.250	0.818
Three	0.002	0.009	0.250	0.200	0.399	0.125	0.375	0.091
Four	0.002	0.009	0.250	0.001	0.001	0.000	0.125	0.091
Number of lanes	Preceding roadway: merge							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
One	0.250	0.250	0.250	0.250	0.250	0.031	0.031	0.250
Two	0.250	0.250	0.250	0.250	0.250	0.031	0.031	0.250
Three	0.250	0.250	0.250	0.250	0.250	0.031	0.031	0.250
Four	0.250	0.250	0.250	0.250	0.250	0.906	0.906	0.250
Number of lanes	Preceding roadway: deceleration lane							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
One	0.972	0.031	0.988	0.832	0.997	0.906	0.332	0.250
Two	0.009	0.906	0.004	0.167	0.001	0.031	0.660	0.250
Three	0.009	0.031	0.004	0.001	0.001	0.031	0.004	0.250
Four	0.009	0.031	0.004	0.001	0.001	0.031	0.004	0.250
Number of lanes	Preceding roadway: fork							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
One	0.250	0.250	0.906	0.972	0.491	0.399	0.009	0.031
Two	0.250	0.250	0.031	0.009	0.491	0.598	0.972	0.906
Three	0.250	0.250	0.031	0.009	0.009	0.001	0.009	0.031
Four	0.250	0.250	0.031	0.009	0.009	0.001	0.009	0.031
Number of lanes	Preceding roadway: weaving section							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
One	0.999	0.988	0.250	0.988	0.399	0.250	0.009	0.250
Two	0.000	0.004	0.250	0.004	0.200	0.498	0.972	0.250
Three	0.000	0.004	0.250	0.004	0.399	0.250	0.009	0.250
Four	0.000	0.004	0.250	0.004	0.001	0.002	0.009	0.250

Table 7
CPT of node "direction".

Direction	Advice speed: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.050	0.008	0.938	0.938	0.500	0.500	0.500	0.500
Right	0.950	0.992	0.063	0.063	0.500	0.500	0.500	0.500
Direction	Advice speed: 60 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.008	0.981	0.664	0.500	0.500	0.500	0.500	0.500
Right	0.992	0.019	0.336	0.500	0.500	0.500	0.500	0.500
Direction	Advice speed: 70 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.500	0.500	0.938	0.400	0.500	0.938	0.500	0.500
Right	0.500	0.500	0.063	0.600	0.500	0.063	0.500	0.500
Direction	Advice speed: 80 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.500	0.500	0.500	0.500	0.938	0.500	0.500	0.500
Right	0.500	0.500	0.500	0.500	0.063	0.500	0.500	0.500
Direction	Advice speed: 90 km/h							

(*continued on next page*)

Table 7 (*continued*)

Direction	Advice speed: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.500	0.500	0.500	0.938	0.500	0.981	0.664	0.500
Right	0.500	0.500	0.500	0.063	0.500	0.019	0.336	0.500
Direction	Speed limit: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.008	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Right	0.992	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Direction	Speed limit: 60 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.500	0.063	0.500	0.500	0.500	0.500	0.500	0.500
Right	0.500	0.938	0.500	0.500	0.500	0.500	0.500	0.500
Direction	Speed limit: 70 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.500	0.500	0.063	0.992	0.334	0.500	0.500	0.500
Right	0.500	0.500	0.938	0.008	0.666	0.500	0.500	0.500
Direction	Speed limit: 80 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.500	0.500	0.500	0.063	0.664	0.500	0.500	0.500
Right	0.500	0.500	0.500	0.938	0.336	0.500	0.500	0.500
Direction	Speed limit: 90 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Right	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Direction	No speed limit							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Left	0.001	0.008	0.019	0.000	0.250	0.261	0.250	0.500
Right	0.999	0.992	0.981	1.000	0.750	0.739	0.750	0.500

Table 8
CPT of node "Curve sign".

Curve sign	Advice speed: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.750	0.992	0.938	0.938	0.500	0.500	0.500	0.500
Not present	0.250	0.008	0.063	0.063	0.500	0.500	0.500	0.500
Curve sign	Advice speed: 60 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.664	0.981	0.992	0.500	0.500	0.500	0.500	0.500
Not present	0.336	0.019	0.008	0.500	0.500	0.500	0.500	0.500
Curve sign	Advice speed: 70 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.063	0.600	0.500	0.063	0.500	0.500
Not present	0.500	0.500	0.938	0.400	0.500	0.938	0.500	0.500
Curve sign	Advice speed: 80 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.500	0.500	0.063	0.981	0.500	0.500
Not present	0.500	0.500	0.500	0.500	0.938	0.019	0.500	0.500
Curve sign	Advice speed: 90 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.500	0.063	0.500	0.500	0.664	0.500
Not present	0.500	0.500	0.500	0.938	0.500	0.500	0.336	0.500
Curve sign	Speed limit: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.664	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Not present	0.336	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Curve sign	Speed limit: 60 km/h							

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Table 8 (*continued*)

Curve sign	Advice speed: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.938	0.500	0.500	0.500	0.500	0.500	0.500
Not present	0.500	0.063	0.500	0.500	0.500	0.500	0.500	0.500
Curve sign	Speed limit: 70 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.938	0.664	0.168	0.500	0.019	0.500
Not present	0.500	0.500	0.063	0.336	0.832	0.500	0.981	0.500
Curve sign	Speed limit: 80 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.500	0.938	0.008	0.500	0.500	0.500
Not present	0.500	0.500	0.500	0.063	0.992	0.500	0.500	0.500
Curve sign	Speed limit: 90 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.019
Not present	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.981
Curve sign	No speed limit							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.832	0.008	0.019	0.267	0.150	0.044	0.000	0.100
Not present	0.168	0.992	0.981	0.733	0.850	0.956	1.000	0.900

Table 9
CPT of node "Preceding roadway type".

Preceding roadway type	Advice speed: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.196	0.331	0.896	0.896	0.167	0.167	0.167	0.167
Main carriageway	0.341	0.331	0.021	0.021	0.167	0.167	0.167	0.167
Merge	0.037	0.003	0.021	0.021	0.167	0.167	0.167	0.167
Deceleration lane	0.204	0.331	0.021	0.021	0.167	0.167	0.167	0.167
Fork	0.012	0.003	0.021	0.021	0.167	0.167	0.167	0.167
Weaving section	0.212	0.003	0.021	0.021	0.167	0.167	0.167	0.167
Preceding roadway type	Advice speed: 60 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.331	0.969	0.659	0.167	0.167	0.167	0.167	0.167
Main carriageway	0.331	0.006	0.003	0.167	0.167	0.167	0.167	0.167
Merge	0.003	0.006	0.003	0.167	0.167	0.167	0.167	0.167
Deceleration lane	0.003	0.006	0.331	0.167	0.167	0.167	0.167	0.167
Fork	0.003	0.006	0.003	0.167	0.167	0.167	0.167	0.167
Weaving section	0.331	0.006	0.003	0.167	0.167	0.167	0.167	0.167
Preceding roadway type	Advice speed: 70 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.167	0.167	0.896	0.399	0.969	0.021	0.167	0.167
Main carriageway	0.167	0.167	0.021	0.399	0.006	0.896	0.167	0.167
Merge	0.167	0.167	0.021	0.001	0.006	0.021	0.167	0.167
Deceleration lane	0.167	0.167	0.021	0.001	0.006	0.021	0.167	0.167
Fork	0.167	0.167	0.021	0.001	0.006	0.021	0.167	0.167
Weaving section	0.167	0.167	0.021	0.200	0.006	0.021	0.167	0.167
Preceding roadway type	Advice speed: 80 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.167	0.167	0.167	0.167	0.896	0.006	0.167	0.167
Main carriageway	0.167	0.167	0.167	0.167	0.021	0.488	0.167	0.167
Merge	0.167	0.167	0.167	0.167	0.021	0.006	0.167	0.167
Deceleration lane	0.167	0.167	0.167	0.167	0.021	0.006	0.167	0.167
Fork	0.167	0.167	0.167	0.167	0.021	0.006	0.167	0.167
Weaving section	0.167	0.167	0.167	0.167	0.021	0.488	0.167	0.167
Preceding roadway type	Advice speed: 90 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.167	0.167	0.167	0.896	0.006	0.006	0.003	0.167
Main carriageway	0.167	0.167	0.167	0.021	0.488	0.006	0.659	0.167

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Table 9 (*continued*)

Preceding roadway type	Advice speed: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Merge	0.167	0.167	0.167	0.021	0.006	0.006	0.003	0.167
Deceleration lane	0.167	0.167	0.167	0.021	0.488	0.006	0.003	0.167
Fork	0.167	0.167	0.167	0.021	0.006	0.488	0.331	0.167
Weaving section	0.167	0.167	0.167	0.021	0.006	0.488	0.003	0.167
Preceding roadway type	Speed limit: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.003	0.167	0.488	0.167	0.167	0.167	0.167	0.167
Main carriageway	0.331	0.167	0.006	0.167	0.167	0.167	0.167	0.167
Merge	0.003	0.167	0.006	0.167	0.167	0.167	0.167	0.167
Deceleration lane	0.331	0.167	0.006	0.167	0.167	0.167	0.167	0.167
Fork	0.003	0.167	0.488	0.167	0.167	0.167	0.167	0.167
Weaving section	0.331	0.167	0.006	0.167	0.167	0.167	0.167	0.167
Preceding roadway type	Speed limit:60 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.167	0.021	0.167	0.167	0.167	0.167	0.167	0.167
Main carriageway	0.167	0.896	0.167	0.167	0.167	0.167	0.167	0.167
Merge	0.167	0.021	0.167	0.167	0.167	0.167	0.167	0.167
Deceleration lane	0.167	0.021	0.167	0.167	0.167	0.167	0.167	0.167
Fork	0.167	0.021	0.167	0.167	0.167	0.167	0.167	0.167
Weaving section	0.167	0.021	0.167	0.167	0.167	0.167	0.167	0.167
Preceding roadway type	Speed limit: 70 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.167	0.167	0.021	0.331	0.499	0.167	0.006	0.167
Main carriageway	0.167	0.167	0.021	0.659	0.167	0.167	0.488	0.167
Merge	0.167	0.167	0.021	0.003	0.000	0.167	0.006	0.167
Deceleration lane	0.167	0.167	0.896	0.003	0.167	0.167	0.488	0.167
Fork	0.167	0.167	0.021	0.003	0.167	0.167	0.006	0.167
Weaving section	0.167	0.167	0.021	0.003	0.000	0.167	0.006	0.167
Preceding roadway type	Speed limit: 80 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.167	0.167	0.167	0.896	0.659	0.167	0.167	0.167
Main carriageway	0.167	0.167	0.167	0.021	0.003	0.167	0.167	0.167
Merge	0.167	0.167	0.167	0.021	0.003	0.167	0.167	0.167
Deceleration lane	0.167	0.167	0.167	0.021	0.003	0.167	0.167	0.167
Fork	0.167	0.167	0.167	0.021	0.331	0.167	0.167	0.167
Weaving section	0.167	0.167	0.167	0.021	0.003	0.167	0.167	0.167
Preceding roadway type	Speed limit: 90 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.006
Main carriageway	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.969
Merge	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.006
Deceleration lane	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.006
Fork	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.006
Weaving section	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.006
Preceding roadway type	No speed sign present							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Connector road	0.333	0.003	0.488	0.267	0.450	0.391	0.083	0.000
Main carriageway	0.000	0.003	0.006	0.067	0.150	0.261	0.417	0.899
Merge	0.000	0.003	0.006	0.000	0.000	0.043	0.083	0.000
Deceleration lane	0.000	0.003	0.488	0.400	0.150	0.043	0.167	0.000
Fork	0.000	0.003	0.006	0.133	0.000	0.174	0.083	0.100
Weaving section	0.665	0.987	0.006	0.133	0.250	0.087	0.167	0.000

Table 10
CPT of node "Expected safe speed".

Expected safe speed (km/h)	
060–069	0.111
070–079	0.059
080–089	0.066
090–099	0.170
100–109	0.222
110–119	0.183
120–129	0.111
130–140	0.079

Table 11
CPT of node "Speed sign".

Speed sign	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Advice speed 50 km/h	0.278	0.333	0.100	0.038	0.000	0.000	0.000	0.000
Advice speed 60 km/h	0.167	0.222	0.300	0.000	0.000	0.000	0.000	0.000
Advice speed 70 km/h	0.009	0.000	0.100	0.192	0.059	0.036	0.000	0.000
Advice speed 80 km/h	0.001	0.000	0.000	0.000	0.029	0.071	0.000	0.000
Advice speed 90 km/h	0.001	0.000	0.000	0.038	0.059	0.071	0.176	0.000
Speed limit 50 km/h	0.175	0.000	0.200	0.000	0.000	0.000	0.000	0.000
Speed limit 60 km/h	0.005	0.111	0.000	0.000	0.000	0.000	0.000	0.000
Speed limit 70 km/h	0.008	0.000	0.100	0.115	0.176	0.000	0.118	0.000
Speed limit 80 km/h	0.009	0.000	0.000	0.038	0.088	0.000	0.000	0.000
Speed limit 90 km/h	0.006	0.000	0.000	0.000	0.000	0.000	0.000	0.167
No speed sign present	0.340	0.333	0.200	0.577	0.588	0.821	0.706	0.833

Table 12
CPT of node "Preceding curve speed".

Preceding curve speed (km/h)	Preceding roadway: connector road							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
060–080	0.231	0.003	0.001	0.000	0.000	0.111	0.025	0.200
080–100	0.048	0.331	0.333	0.300	0.118	0.111	0.025	0.200
100–120	0.449	0.331	0.333	0.500	0.471	0.444	0.025	0.200
120–140	0.053	0.003	0.167	0.000	0.118	0.000	0.900	0.200
Tangent	0.219	0.331	0.167	0.200	0.294	0.333	0.025	0.200
Preceding curve speed (km/h)	Preceding roadway: main carriageway							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
060–080	0.002	0.007	0.200	0.001	0.001	0.000	0.000	0.000
080–100	0.250	0.007	0.200	0.001	0.399	0.125	0.000	0.000
100–120	0.002	0.007	0.200	0.598	0.001	0.125	0.000	0.000
120–140	0.002	0.007	0.200	0.001	0.200	0.125	0.375	0.182
Tangent	0.746	0.970	0.200	0.399	0.399	0.624	0.624	0.818
Preceding curve speed (km/h)	Preceding roadway: merge							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
060–080	0.200	0.200	0.200	0.200	0.200	0.025	0.025	0.200
080–100	0.200	0.200	0.200	0.200	0.200	0.025	0.025	0.200
100–120	0.200	0.200	0.200	0.200	0.200	0.025	0.025	0.200
120–140	0.200	0.200	0.200	0.200	0.200	0.025	0.025	0.200
Tangent	0.200	0.200	0.200	0.200	0.200	0.900	0.900	0.200
Preceding curve speed (km/h)	Preceding roadway: deceleration lane							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
060–080	0.007	0.025	0.003	0.001	0.001	0.025	0.003	0.200
080–100	0.007	0.025	0.003	0.001	0.001	0.025	0.003	0.200
100–120	0.007	0.025	0.003	0.001	0.001	0.025	0.003	0.200
120–140	0.007	0.025	0.003	0.001	0.001	0.025	0.003	0.200
Tangent	0.970	0.900	0.988	0.998	0.996	0.900	0.988	0.200

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Table 12 (*continued*)

Preceding curve speed (km/h)	Preceding roadway: connector road							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Preceding curve speed (km/h)	Preceding roadway: fork							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
060–080	0.200	0.200	0.025	0.007	0.007	0.001	0.007	0.025
080–100	0.200	0.200	0.025	0.007	0.007	0.001	0.007	0.025
100–120	0.200	0.200	0.025	0.007	0.007	0.001	0.007	0.025
120–140	0.200	0.200	0.025	0.007	0.007	0.001	0.007	0.025
Tangent	0.200	0.200	0.900	0.970	0.970	0.996	0.970	0.900
Preceding curve speed (km/h)	Preceding roadway: weaving section							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
060–080	0.000	0.003	0.200	0.003	0.001	0.002	0.007	0.200
080–100	0.000	0.003	0.200	0.003	0.001	0.002	0.007	0.200
100–120	0.000	0.003	0.200	0.003	0.001	0.002	0.007	0.200
120–140	0.000	0.003	0.200	0.003	0.001	0.002	0.007	0.200
Tangent	0.998	0.988	0.200	0.988	0.996	0.994	0.970	0.200

Table 13
CPT of node "Curve angle".

Curve angle (grad)	Preceding curve speed: 060–080 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
010–100	0.114	0.333	0.333	0.333	0.333	0.792	0.333	0.333
100–200	0.549	0.333	0.333	0.333	0.333	0.167	0.333	0.333
200–300	0.336	0.333	0.333	0.333	0.333	0.042	0.333	0.333
Curve angle (grad)	Preceding curve speed: 080–100 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
010–100	0.042	0.167	0.086	0.943	0.731	0.901	0.333	0.333
100–200	0.042	0.792	0.901	0.052	0.267	0.086	0.333	0.333
200–300	0.917	0.042	0.012	0.005	0.003	0.012	0.333	0.333
Curve angle (grad)	Preceding curve speed: 100–120 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
010–100	0.012	0.042	0.086	0.132	0.622	0.974	0.333	0.333
100–200	0.012	0.042	0.901	0.743	0.378	0.025	0.333	0.333
200–300	0.975	0.917	0.012	0.125	0.000	0.002	0.333	0.333
Curve angle (grad)	Preceding curve speed: 120–140 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
010–100	0.333	0.333	0.167	0.333	0.052	0.167	0.963	0.901
100–200	0.333	0.333	0.792	0.333	0.943	0.792	0.035	0.086
200–300	0.333	0.333	0.042	0.333	0.005	0.042	0.003	0.012
Curve angle (grad)	Preceding curve speed: tangent							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
010–100	0.001	0.141	0.404	0.599	0.893	0.631	0.538	0.795
100–200	0.230	0.003	0.594	0.401	0.107	0.369	0.462	0.205
200–300	0.769	0.856	0.002	0.000	0.000	0.000	0.000	0.000

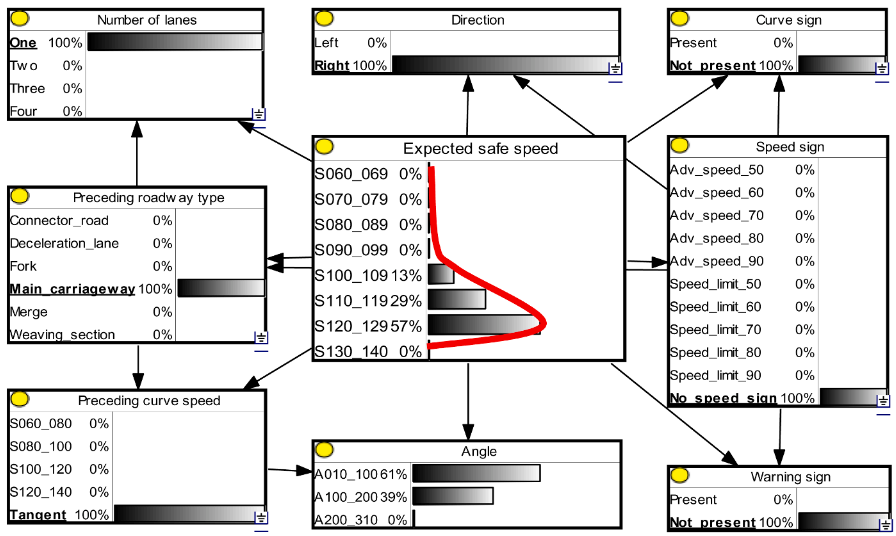
Table 14
CPT of node “Warning sign”.

Warning sign	Advice speed: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.707	0.992	0.938	0.938	0.500	0.500	0.500	0.500
Not present	0.293	0.008	0.063	0.063	0.500	0.500	0.500	0.500
Warning sign	Advice speed: 60 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.664	0.981	0.992	0.500	0.500	0.500	0.500	0.500
Not present	0.336	0.019	0.008	0.500	0.500	0.500	0.500	0.500
Warning sign	Advice speed: 70 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.063	0.799	0.981	0.063	0.500	0.500
Not present	0.500	0.500	0.938	0.201	0.019	0.938	0.500	0.500
Warning sign	Advice speed: 80 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.500	0.500	0.938	0.981	0.500	0.500
Not present	0.500	0.500	0.500	0.500	0.063	0.019	0.500	0.500
Warning sign	Advice speed: 90 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.500	0.063	0.981	0.500	0.992	0.500
Not present	0.500	0.500	0.500	0.938	0.019	0.500	0.008	0.500
Warning sign	Speed limit: 50 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.664	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Not present	0.336	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Warning sign	Speed limit: 60 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.938	0.500	0.500	0.500	0.500	0.500	0.500
Not present	0.500	0.063	0.500	0.500	0.500	0.500	0.500	0.500
Warning sign	Speed limit: 70 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.063	0.664	0.334	0.500	0.500	0.500
Not present	0.500	0.500	0.938	0.336	0.666	0.500	0.500	0.500
Warning sign	Speed limit: 80 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.500	0.938	0.008	0.500	0.500	0.500
Not present	0.500	0.500	0.500	0.063	0.992	0.500	0.500	0.500
Warning sign	Speed limit: 90 km/h							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Not present	0.500	0.500	0.500	0.500	0.500	0.500	0.500	0.500
Warning sign	No speed limit							
	Expected safe speed (km/h)							
	060–069	070–079	080–089	090–099	100–109	110–119	120–129	130–140
Present	0.001	0.008	0.019	0.067	0.100	0.087	0.000	0.100
Not present	0.999	0.992	0.981	0.933	0.900	0.913	1.000	0.900

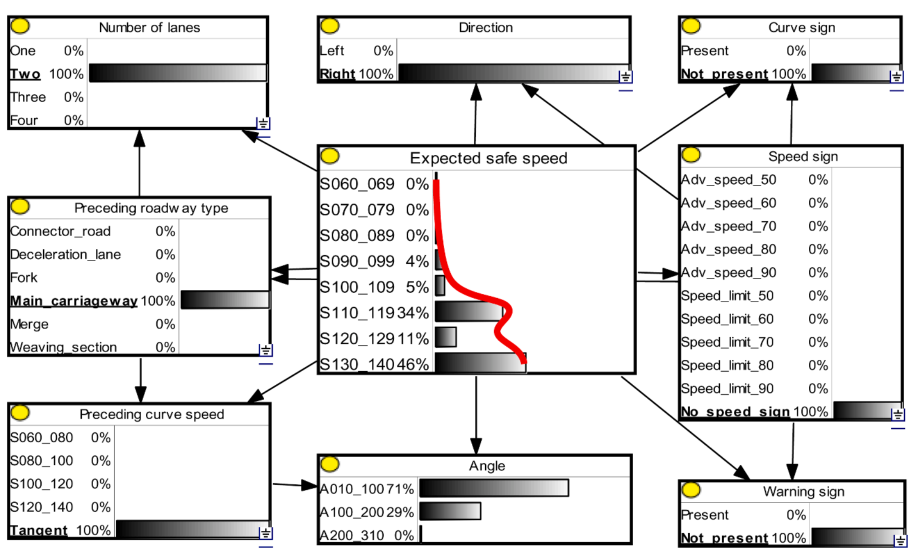
Appendix B. – Some relevant safe speed expectations

The letters to the left of the TANs represent the letters in Table 5.

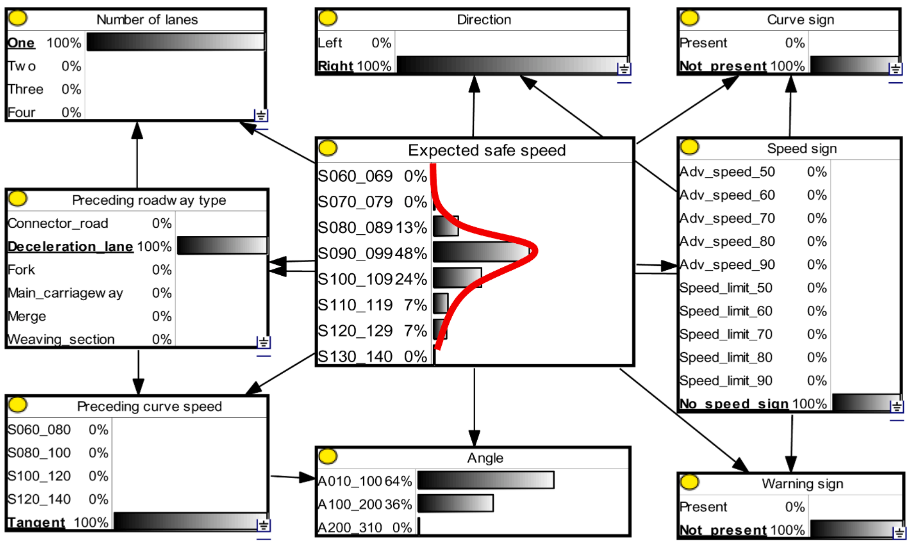
A



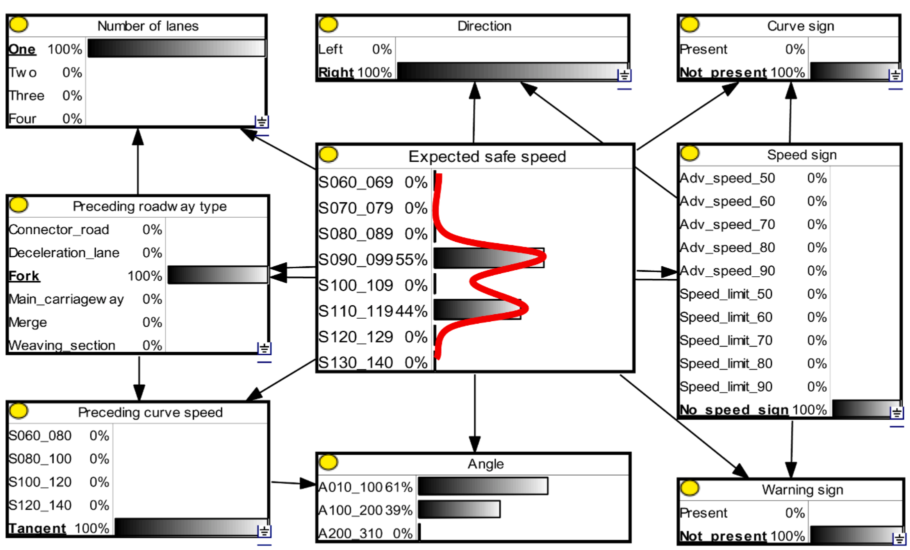
B



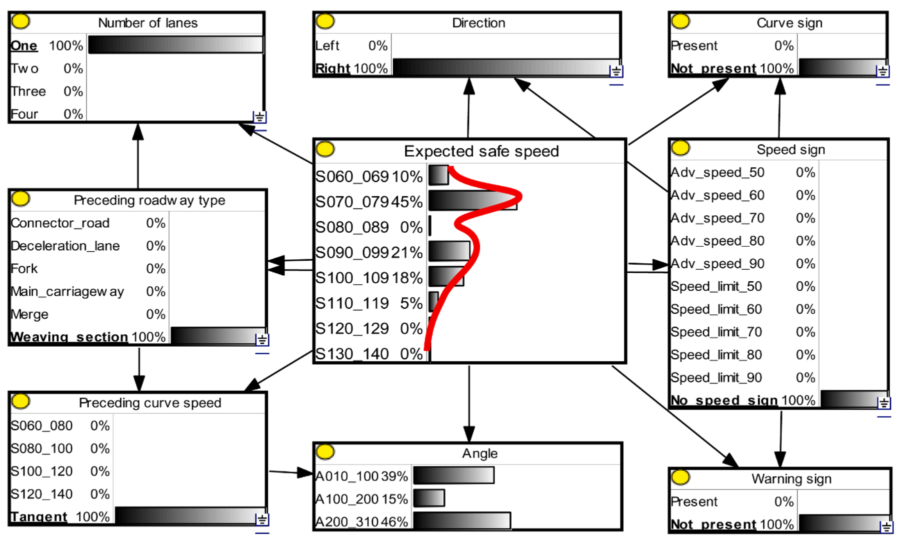
C


Number of lanes
One 100%
Two 0%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 0%
Not present 100%
Expected safe speed
S060_069 0%
S070_079 0%
S080_089 13%
S090_099 48%
S100_109 24%
S110_119 7%
S120_129 7%
S130_140 0%
Speed sign
Adv_speed_50 0%
Adv_speed_60 0%
Adv_speed_70 0%
Adv_speed_80 0%
Adv_speed_90 0%
Speed_limit_50 0%
Speed_limit_60 0%
Speed_limit_70 0%
Speed_limit_80 0%
Speed_limit_90 0%
No speed sign 100%
Preceding roadway type
Connector_road 0%
Deceleration_lane 100%
Fork 0%
Main_carriageway 0%
Merge 0%
Weaving_section 0%
Preceding curve speed
S060_080 0%
S080_100 0%
S100_120 0%
S120_140 0%
Tangent 100%
Angle
A010_100 64%
A100_200 36%
A200_310 0%
Warning sign
Present 0%
Not present 100%

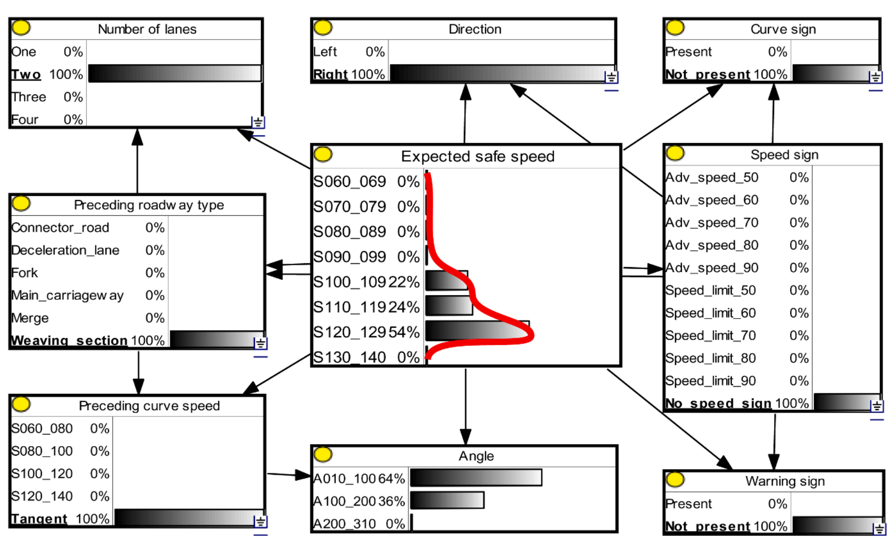
D

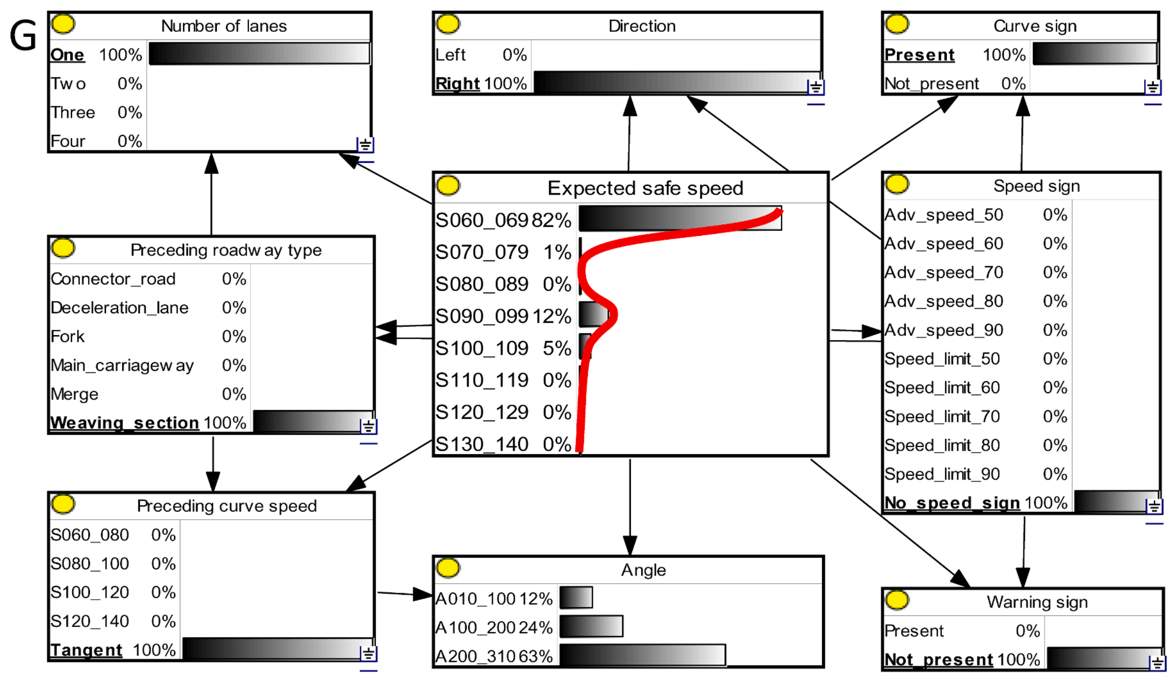

Number of lanes
One 100%
Two 0%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 0%
Not present 100%
Expected safe speed
S060_069 0%
S070_079 0%
S080_089 0%
S090_099 55%
S100_109 0%
S110_119 44%
S120_129 0%
S130_140 0%
Speed sign
Adv_speed_50 0%
Adv_speed_60 0%
Adv_speed_70 0%
Adv_speed_80 0%
Adv_speed_90 0%
Speed_limit_50 0%
Speed_limit_60 0%
Speed_limit_70 0%
Speed_limit_80 0%
Speed_limit_90 0%
No speed sign 100%
Preceding roadway type
Connector_road 0%
Deceleration_lane 0%
Fork 100%
Main_carriageway 0%
Merge 0%
Weaving_section 0%
Preceding curve speed
S060_080 0%
S080_100 0%
S100_120 0%
S120_140 0%
Tangent 100%
Angle
A010_100 61%
A100_200 39%
A200_310 0%
Warning sign
Present 0%
Not present 100%

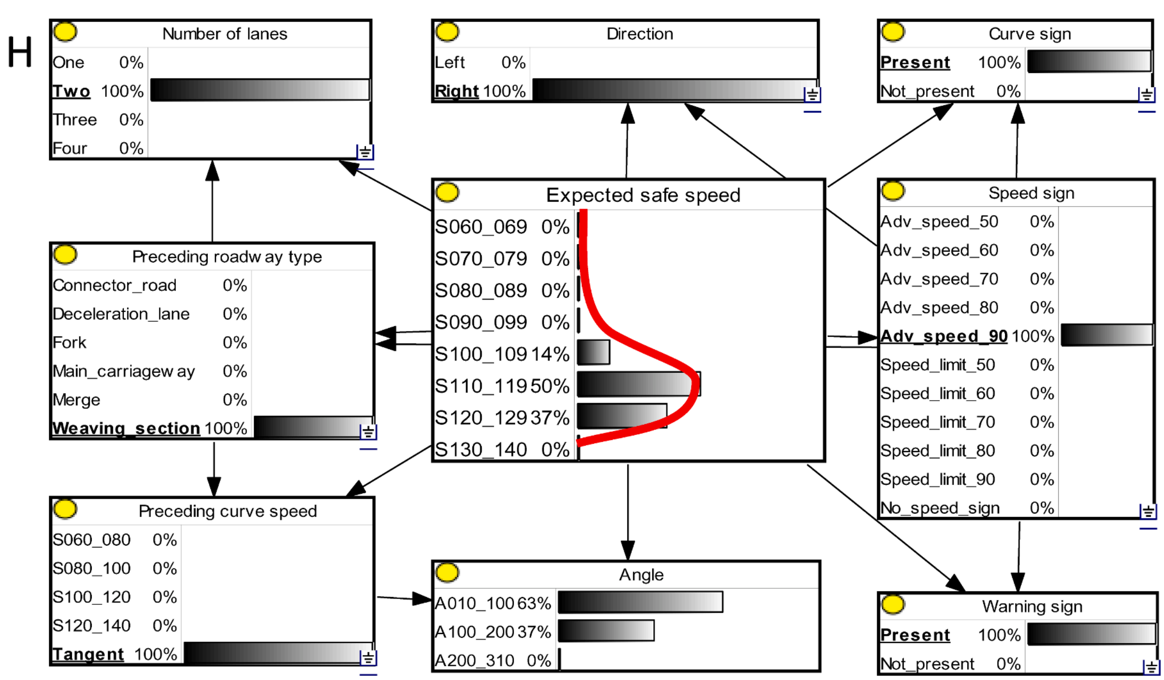
E


Number of lanes
One 100%
Two 0%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 0%
Not present 100%
Expected safe speed
S060_069 10%
S070_079 45%
S080_089 0%
S090_099 21%
S100_109 18%
S110_119 5%
S120_129 0%
S130_140 0%
Preceding roadway type
Connector_road 0%
Deceleration_lane 0%
Fork 0%
Main_carriageway 0%
Merge 0%
Weaving_section 100%
Speed sign
Adv_speed_50 0%
Adv_speed_60 0%
Adv_speed_70 0%
Adv_speed_80 0%
Adv_speed_90 0%
Speed_limit_50 0%
Speed_limit_60 0%
Speed_limit_70 0%
Speed_limit_80 0%
Speed_limit_90 0%
No_speed_sign 100%
Preceding curve speed
S060_080 0%
S080_100 0%
S100_120 0%
S120_140 0%
Tangent 100%
Angle
A010_100 39%
A100_200 15%
A200_310 46%
Warning sign
Present 0%
Not present 100%

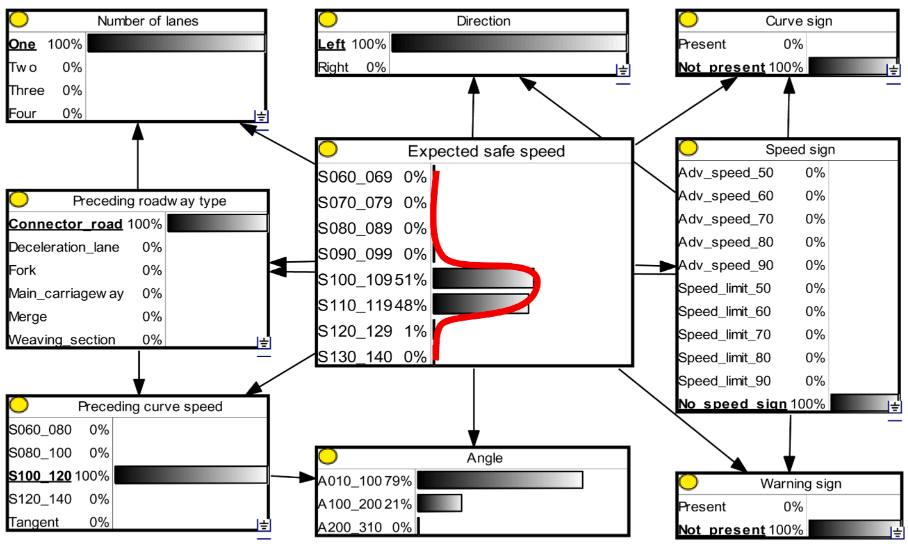
F


Number of lanes
One 0%
Two 100%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 0%
Not present 100%
Expected safe speed
S060_069 0%
S070_079 0%
S080_089 0%
S090_099 0%
S100_109 22%
S110_119 24%
S120_129 54%
S130_140 0%
Preceding roadway type
Connector_road 0%
Deceleration_lane 0%
Fork 0%
Main_carriageway 0%
Merge 0%
Weaving_section 100%
Speed sign
Adv_speed_50 0%
Adv_speed_60 0%
Adv_speed_70 0%
Adv_speed_80 0%
Adv_speed_90 0%
Speed_limit_50 0%
Speed_limit_60 0%
Speed_limit_70 0%
Speed_limit_80 0%
Speed_limit_90 0%
No_speed_sign 100%
Preceding curve speed
S060_080 0%
S080_100 0%
S100_120 0%
S120_140 0%
Tangent 100%
Angle
A010_100 64%
A100_200 36%
A200_310 0%
Warning sign
Present 0%
Not present 100%

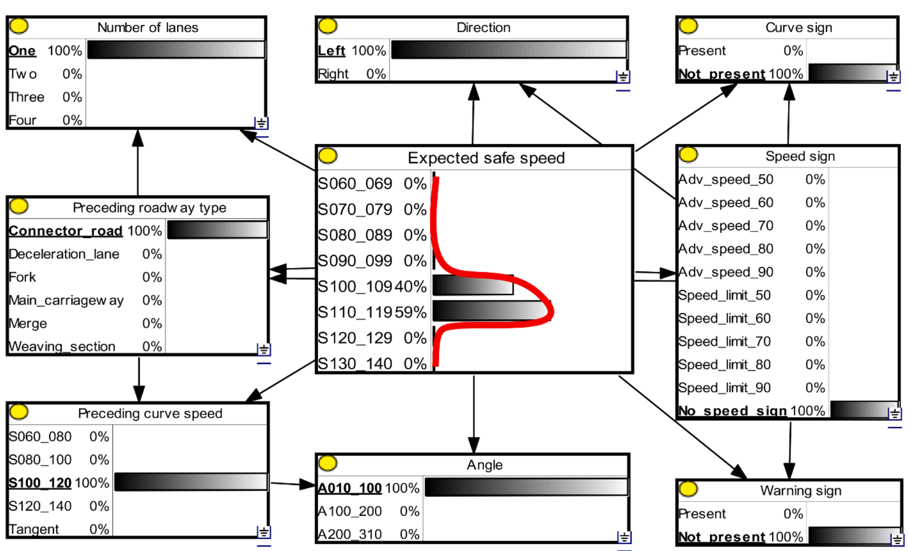

G
Number of lanes
One 100%
Two 0%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 100%
Not_present 0%
Expected safe speed
S060_069 82%
S070_079 1%
S080_089 0%
S090_099 12%
S100_109 5%
S110_119 0%
S120_129 0%
S130_140 0%
Speed sign
Adv_speed_50 0%
Adv_speed_60 0%
Adv_speed_70 0%
Adv_speed_80 0%
Adv_speed_90 0%
Speed_limit_50 0%
Speed_limit_60 0%
Speed_limit_70 0%
Speed_limit_80 0%
Speed_limit_90 0%
No_speed_sign 100%
Preceding roadway type
Connector_road 0%
Deceleration_lane 0%
Fork 0%
Main_carriageway 0%
Merge 0%
Weaving_section 100%
Preceding curve speed
S060_080 0%
S080_100 0%
S100_120 0%
S120_140 0%
Tangent 100%
Angle
A010_100 12%
A100_200 24%
A200_310 63%
Warning sign
Present 0%
Not_present 100%

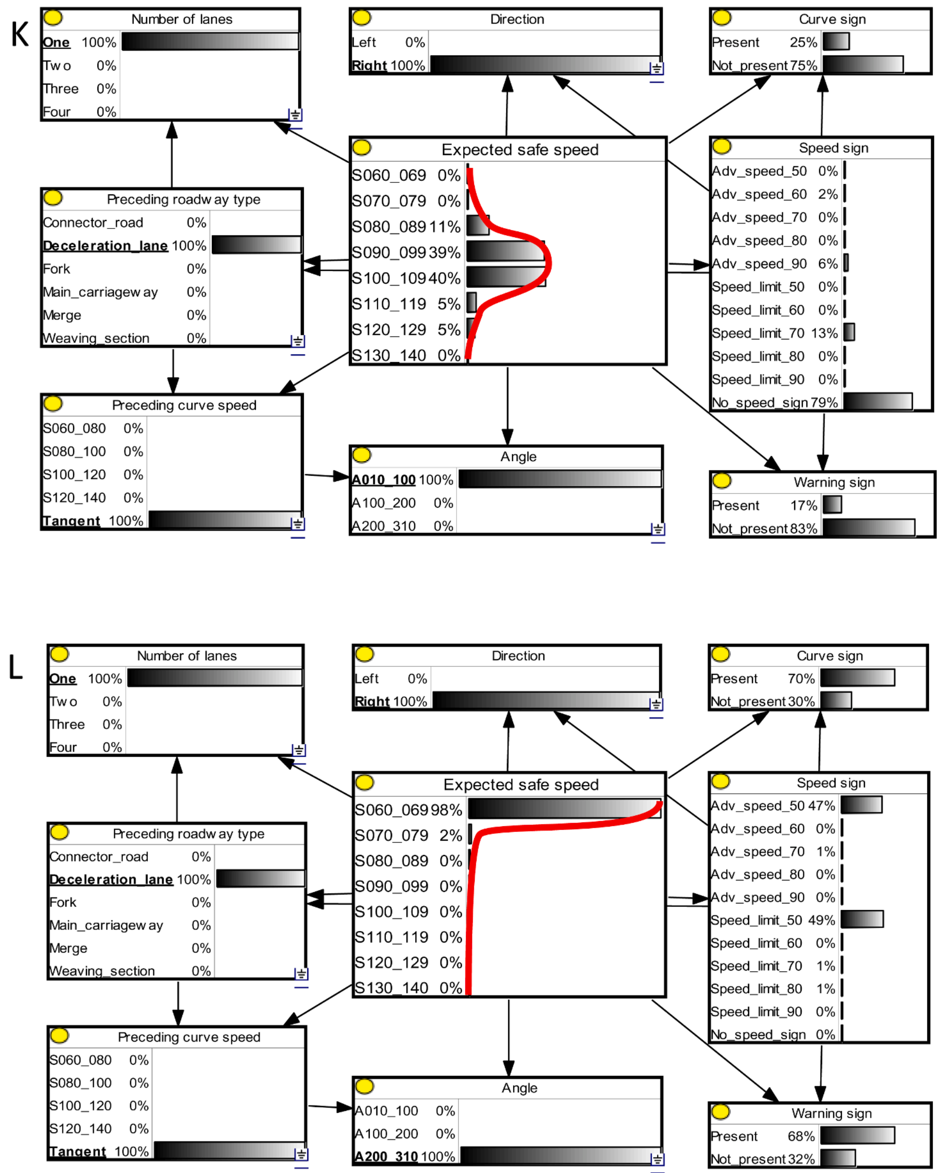

H
Number of lanes
One 0%
Two 100%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 100%
Not_present 0%
Expected safe speed
S060_069 0%
S070_079 0%
S080_089 0%
S090_099 0%
S100_109 14%
S110_119 50%
S120_129 37%
S130_140 0%
Speed sign
Adv_speed_50 0%
Adv_speed_60 0%
Adv_speed_70 0%
Adv_speed_80 0%
Adv_speed_90 100%
Speed_limit_50 0%
Speed_limit_60 0%
Speed_limit_70 0%
Speed_limit_80 0%
Speed_limit_90 0%
No_speed_sign 0%
Preceding roadway type
Connector_road 0%
Deceleration_lane 0%
Fork 0%
Main_carriageway 0%
Merge 0%
Weaving_section 100%
Preceding curve speed
S060_080 0%
S080_100 0%
S100_120 0%
S120_140 0%
Tangent 100%
Angle
A010_100 63%
A100_200 37%
A200_310 0%
Warning sign
Present 100%
Not_present 0%

I


Number of lanes
One 100%
Two 0%
Three 0%
Four 0%
Direction
Left 100%
Right 0%
Curve sign
Present 0%
Not present 100%
Expected safe speed
S060_069 0%
S070_079 0%
S080_089 0%
S090_099 0%
S100_109 51%
S110_119 48%
S120_129 1%
S130_140 0%
Speed sign
Adv_speed_50 0%
Adv_speed_60 0%
Adv_speed_70 0%
Adv_speed_80 0%
Adv_speed_90 0%
Speed_limit_50 0%
Speed_limit_60 0%
Speed_limit_70 0%
Speed_limit_80 0%
Speed_limit_90 0%
No_speed_sign 100%
Preceding roadway type
Connector_road 100%
Deceleration_lane 0%
Fork 0%
Main_carriageway 0%
Merge 0%
Weaving_section 0%
Preceding curve speed
S060_080 0%
S080_100 0%
S100_120 100%
S120_140 0%
Tangent 0%
Angle
A010_100 79%
A100_200 21%
A200_310 0%
Warning sign
Present 0%
Not present 100%

J


Number of lanes
One 100%
Two 0%
Three 0%
Four 0%
Direction
Left 100%
Right 0%
Curve sign
Present 0%
Not present 100%
Expected safe speed
S060_069 0%
S070_079 0%
S080_089 0%
S090_099 0%
S100_109 40%
S110_119 59%
S120_129 0%
S130_140 0%
Speed sign
Adv_speed_50 0%
Adv_speed_60 0%
Adv_speed_70 0%
Adv_speed_80 0%
Adv_speed_90 0%
Speed_limit_50 0%
Speed_limit_60 0%
Speed_limit_70 0%
Speed_limit_80 0%
Speed_limit_90 0%
No_speed_sign 100%
Preceding roadway type
Connector_road 100%
Deceleration_lane 0%
Fork 0%
Main_carriageway 0%
Merge 0%
Weaving_section 0%
Preceding curve speed
S060_080 0%
S080_100 0%
S100_120 100%
S120_140 0%
Tangent 0%
Angle
A010_100 100%
A100_200 0%
A200_310 0%
Warning sign
Present 0%
Not present 100%



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