Drivers' Behaviour on Freeway Curve Approach
Different Angles, Different Perspectives

Vos, J.

DOI
10.4233/uuid:5a44e49e-6df3-469b-b9a6-f19085188280

Publication date
2024

Document Version
Final published version

Citation (APA)
Vos, J. (2024). *Drivers' Behaviour on Freeway Curve Approach: Different Angles, Different Perspectives*. [Dissertation (TU Delft), Delft University of Technology]. https://doi.org/10.4233/uuid:5a44e49e-6df3-469b-b9a6-f19085188280

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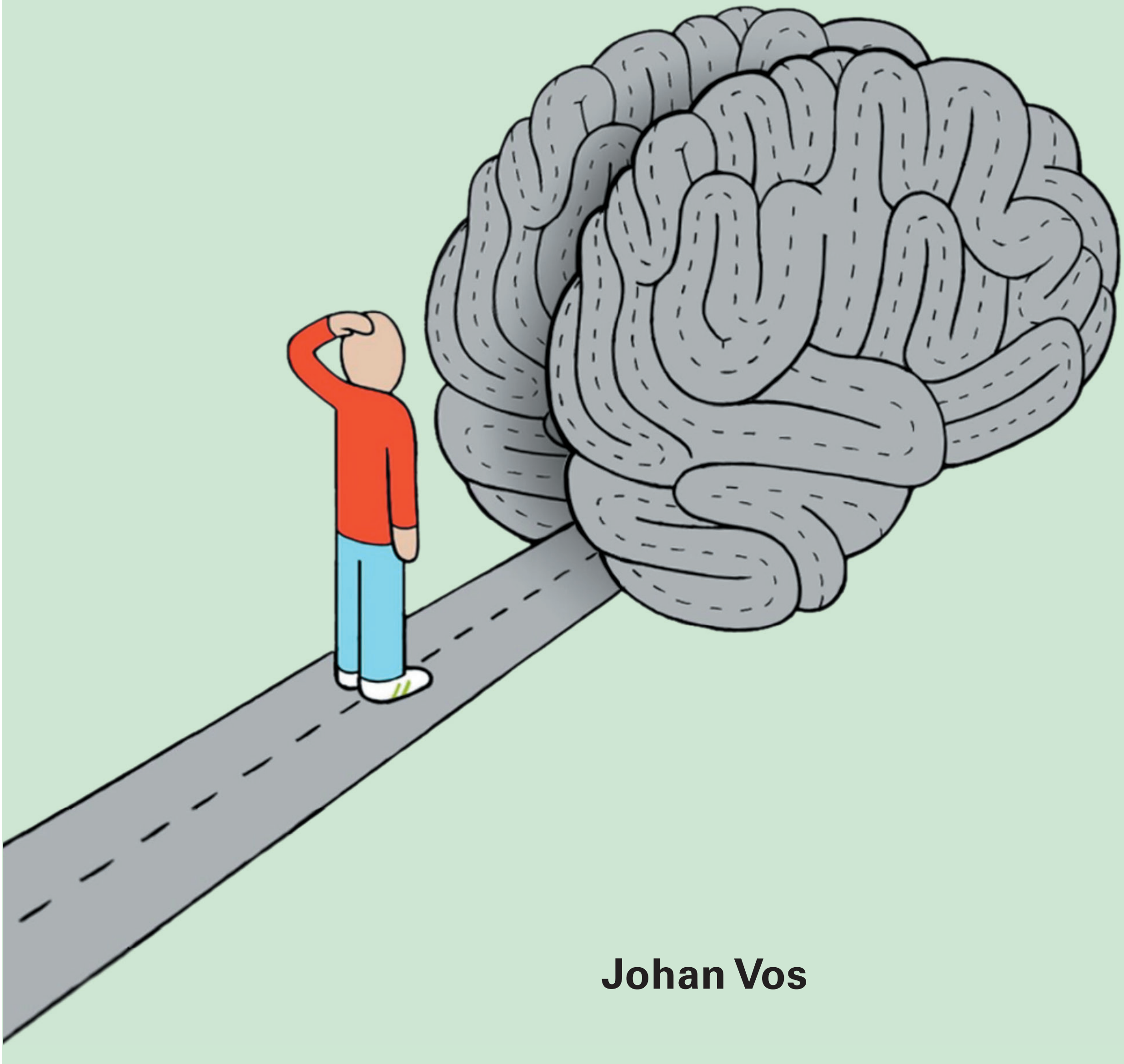

Johan Vos

Drivers' Behaviour on Freeway Curve Approach

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Johan Vos

Delft University of Technology

This research has been funded by Rijkswaterstaat,
the executive agency of the Dutch Ministry of Infrastructure and Water Management.

Rijkswaterstaat
Ministry of Infrastructure and Water Management

Cover illustration by Tomas Schats

Drivers' Behaviour on Freeway Curve Approach

Different Angles, Different Perspectives

Dissertation

for the purpose of obtaining the degree of doctor

at Delft University of Technology,

by the authority of the Rector Magnificus, Prof. dr.ir. T.H.J.J. van der Hagen

chair of the Board for Doctorates,

to be defended publicly on Thursday 8 February 2024 at 15:00 o'clock

by

Johan VOS

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This dissertation has been approved by the promotors.

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TRAIL Thesis Series no. T2024/1, the Netherlands Research School TRAIL

TRAIL
P.O. Box 5017
2600 GA Delft
The Netherlands
E-mail: info@rsTRAIL.nl

ISBN: 978-90-5584-340-4

Printed in the Netherlands

Dedicated to Marleen, Niek, Evi and Rosa

Foreword and Acknowledgements

One of my earliest memories is riding on a tour bus to the work island 'Neeltje Jans' to watch the construction of the storm surge barrier in the Eastern Scheldt around 1984 or 1985. This experience likely sparked my interest in civil engineering at a young age, and my dad further fuelled that interest. He operated a wheel loader on major infrastructure projects at the time and often took me along on Saturdays to show me what he was working on. While the heavy machinery was impressive (and fun to operate), what really fascinated me was the design of interchanges. I filled my school notebooks with fictional interchange designs, constantly trying to recreate and improve upon the ones my dad had shown me. It is no surprise, then, that I decided to pursue a bachelor's education in traffic engineering. This program taught me how to design roads from a traffic perspective, which usually involved implementing established guidelines.

After completing my bachelor's degree, my teachers at Noordelijke Hogeschool Leeuwarden encouraged me to pursue a master's degree. It was during this time at Rijksuniversiteit Groningen that I first delved into scientific study. Learning about environmental and infrastructure planning theories and engaging in discussions was incredibly rewarding, particularly with Jochem about postmodernism and traffic safety (Dijkstra, 2008). While a desire to pursue a PhD had always been in the back of my mind, it seemed out of reach at that point.

In industry, working at Arcadis and Movares, I got to operationalise my knowledge on infrastructural planning and design. At Arcadis, I collaborated with seasoned designers, and at Movares, I had the chance to lead various road designs and delve into human factors. It was during my first major project, widening the N33, that I connected with colleagues at Rijkswaterstaat: Henk Hennink and Ad Kranenburg. They introduced me to the concept of considering the interaction between the driver and the road (human factors) beyond the scope of standard design guidelines, in order to see the design from the driver's perspective. This perspective deeply intrigued me and aligned with my drive to understand every aspect of geometrical road design.

Taking guidance from Chantal Merkx, I enrolled in courses on applied cognitive psychology at Utrecht University. This helped me articulate specific design issues that were not covered by design manuals during road safety audits.

Switching to government opened up some new perspectives. At Rijkswaterstaat (executive agency of the Dutch Ministry of Infrastructure) I got to oversee the Dutch guidelines on geometric design of freeways, known as the ROA. Here I learned that the understanding of geometric design is still evolving. My colleagues Jaap Groot and Gerald Uittenbogerd had been using High Frequency Floating Car Data to correlate speed profiles along off ramps with curve geometry. This made me realise how the guidelines were not reflecting actual use of our freeways, but were based on research done decades ago.

The lingering wish to pursue a PhD was sparked again while attending the PhD defence of Billie (de Haas, 2017). Recognizing the opportunities at Rijkswaterstaat, and with the support of my colleague Jurgen Koppen, I started to write a research proposal and collect additional funding. During this period, I delved into old Dutch papers from the 1960's and 1970's describing early Dutch research on freeway design and tried to update my knowledge on cognitive psychology to get a better grasp at the topic in mind: driver behaviour at freeway curves.

Most of the research proposal was written from the comfort of my home, and I discussed it with Marjan Hagenzieker and Haneen Farah, whom I approached as potential supervisors. Their expertise in applied psychology, road infrastructure design and methodology, coupled with their enthusiasm for my topic, helped me create the initial outline of my research. After several discussions, my PhD journey officially commenced on January 1st, 2019. Even though I had prepared the proposal, it still felt like venturing into uncharted territory. Rijkswaterstaat allocated one day a week for my research and after about a year and a half in, I dedicated additional time, as by then all my children were in school. This required careful planning at home, and I am immensely grateful that Marleen and I devised a schedule that allowed me to pursue my PhD while also supporting Marleen in her aspirations as a writer.

In my initial research, I relied on an online survey as the primary methodology. Therefore, my first paper would not have been possible without the support of friends and colleagues who shared the survey in their own networks. I am aware of the dedication that some of you showed in spreading and completing the survey, and I am sincerely grateful for your efforts.

Conducting my on-road study required significant time and effort from the participants. I am grateful for your participation, especially since it turned out to be more challenging than anticipated to find a sufficient number of participants. So I want to extend my gratitude to Iris Welvaarts from the ANWB for also reaching out to ANWB members for this study.

For my speed prediction modelling, I compiled a substantial database. This achievement would not have been possible without the funding provided by Rijkswaterstaat. I would like to express my thanks to Jurgen Koppen for recognizing the value of this data in enhancing our understanding of speed in curve approaches. I am grateful for his assistance in obtaining the High Frequency Floating Car Data from Be-Mobile, as well as the efficient re-engineering of the road sections carried out by Arcadis.

I want to give special thanks to the data lab team at Be-Mobile for their support in initiating the analysis of the raw data. I had the opportunity to spend valuable time with Lisa, Jan, and Kwinten in Brugge, learning about data analysis.

In the latter half of my PhD journey, I had some insightful discussions with Ilse Harms. Her expertise on familiarity proved valuable in my final two papers.

Throughout my PhD journey, I actively sought feedback from a sounding board at Rijkswaterstaat. Alex, Jaap, Raymond, and Kirsten, I want to express my gratitude for your constructive input and genuine interest. Your contributions ensured that my research closely aligned with Rijkswaterstaat's interests. While at Rijkswaterstaat, I openly shared my ideas, brainfarts, and discussed my findings. Some of the less developed concepts were bounced off my close colleagues in the "geometrical road design" team: Teed, Paul, Hans, and Koen. I appreciate your attentive listening and practical feedback. Furthermore, in various meetings related to signage, traffic safety,

and behaviour, I shared insights aggregated from my research. The discussions during and after these meetings highlighted for me how much I valued the integration of my applied research into discussions relating the knowledge field of road design at Rijkswaterstaat.

Aside from the significant influence my paranymphs had on my research, Jurgen and Chantal were invaluable in assisting with the preparation of my defence. I want to extend my heartfelt thanks for alleviating some of my stress and for showcasing the depth of knowledge we have in traffic safety and human factors at Rijkswaterstaat. I hope to work alongside the both of you for a long time ahead.

Obviously, the quality of my research was greatly enhanced by the guidance of my promotors. Marjan and Haneen, I highly value the discussions we had; they were to the point and incredibly helpful in organizing my thought process. Additionally, discussing the on-road study with Joost de Winter significantly improved my understanding of eye-tracking. I was truly impressed by the amount of work you all put into academia – I deeply appreciate your efforts and hope you also take care of yourselves!

My parents were also reading and trying to understand my research interests. Hendrik-Jan and Adri, thank you so much for your continued support throughout my career. You had the confidence to let me forge my own path, even though it was vastly different from what you were accustomed to. You supported me staying on the HAVO, switching from civil engineering to traffic engineering, being board member of a faculty union at University and so much more. Thank you for your belief in me.

However, this journey would not have been possible without the unwavering support of my wife. Marleen, I deeply love you and would like to thank you immensely for providing the time and patience during these hectic years. I am fully aware of the imbalance my PhD brought to our family. The Covid-lockdowns tested our resilience, but despite the fatigue, we managed to persevere in pursuit of both our ambitions while still making time for each other and our children. Niek, Evi and Rosa, you have seen how I was talking in English with my supervisors during the lockdowns, and you have seen my enthusiasm about freeways. I love you, your down-to-earth views, cuddles, playful moments and so much more. Now, it's time to strike a balance at home and embark on our new journey in our new home – in so many perspectives.

Voorwoord

Eén van mijn vroegste herinneringen is de busrit naar het werkeiland 'Neeltje Jans' om de bouw van de Oosterscheldekering te bekijken, rond 1984 of 1985. Deze ervaring heeft waarschijnlijk mijn interesse in civiele techniek op jonge leeftijd gewekt, en mijn vader heeft die interesse zeker verder aangewakkerd. Hij was destijds shovelmachinist op grote infrastructuurprojecten en nam me vaak op zaterdagen mee om me te laten zien waar hij aan werkte. Hoewel het zware materieel indrukwekkend was (en leuk om te bedienen), fascineerde het *ontwerp* van knooppunten me vooral. Ik vulde mijn schoolschriftjes met fictieve ontwerpen van knooppunten, waarbij ik voortdurend probeerde dat wat ik bij mijn vader had gezien te evenaren en te verbeteren. Het is dan ook geen verrassing dat ik besloot een de HTS verkeerskunde te doen. Daar leerde ik wegen te ontwerpen vanuit een verkeersperspectief, wat meestal het implementeren van vastgestelde richtlijnen inhield.

Na het behalen van mijn bachelorsdiploma moedigden mijn docenten aan de Noordelijke Hogeschool Leeuwarden me aan om een masteropleiding te volgen. Aan de Rijksuniversiteit Groningen ging ik me voor het eerst echt verdiepen in wetenschappelijk onderzoek. Het leren over milieu- en infrastructuurplanningstheorieën en er over discussiëren gaf veel voldoening, vooral met Jochem over postmodernisme en verkeersveiligheid (Dijkstra, 2008). Hoewel de ambitie om een PhD te doen vanaf dat moment in mijn achterhoofd zat, leek het destijds nog buiten bereik.

In de markt, werkend bij Arcadis en Movares, kreeg ik de kans om mijn kennis op het gebied van infrastructuurplanning en -ontwerp toe te passen. Bij Arcadis werkte ik samen met ervaren ontwerpers, en bij Movares kreeg ik de kans om verschillende wegontwerpen te leiden en me te verdiepen in *human factors*. Tijdens mijn eerste grote project, het verbreden van de N33, kwam ik in contact met vakgenoten bij Rijkswaterstaat: Henk Hennink en Ad Kranenburg. Zij introduceerden mij in het denken over de interactie tussen de bestuurder en de weg (human factors) buiten het toepassen van standaard ontwerprichtlijnen om, om het ontwerp vanuit het perspectief van de bestuurder te bekijken. Dit perspectief intrigeerde me en sloot aan bij mijn drang om elk aspect van geometrisch wegontwerp te begrijpen.

Op aanraden van Chantal Merkx schreef ik me daarna in voor cursussen toegepaste cognitieve psychologie aan de Universiteit Utrecht. Dit hielp me om specifieke ontwerpvraagstukken onder woorden te brengen bij verkeersveiligheidsaudits, buiten de ontwerprichtlijnen om.

De overstap naar de overheid opende nieuwe perspectieven. Bij Rijkswaterstaat, kreeg ik de verantwoordelijkheid voor de Nederlandse richtlijnen voor geometrisch ontwerp van autosnelwegen, bekend als de ROA. Hier leerde ik dat het doorgronden van geometrisch ontwerp nog steeds evolueerde. Mijn collega's Jaap Groot en Gerald Uittenbogerd gebruikten High Frequency Floating Car Data om snelheidsprofielen langs afritten te correleren met bochtgeometrie. Dit deed me beseffen dat de richtlijnen niet het daadwerkelijke gebruik van onze autosnelwegen weerspiegelen, maar gebaseerd zijn op onderzoek dat decennia geleden was uitgevoerd.

De sluimerende ambitie om een PhD te doen werd opnieuw aangewakkerd tijdens het bijwonen van de PhD-verdediging van Billie (de Haas, 2017). De mogelijkheden bij Rijkswaterstaat herkennend, en met steun van mijn collega Jurgen Koppen begon ik een onderzoeksvoorstel te schrijven en aanvullende financiering te verzamelen. In deze periode dook ik in oude Nederlandse artikelen uit de jaren 1960 en 1970 die het oude Nederlandse onderzoek naar snelwegontwerp beschreven en probeerde ik mijn kennis van cognitieve psychologie bij te schaven om een beter begrip te krijgen van het onderwerp: het gedrag van bestuurders bij bochten van autosnelwegen.

Het grootste deel van het onderzoeksvoorstel schreef ik thuis op de bank, en ik besprak het met Marjan Hagenzieker en Haneen Farah, die ik benaderde als mogelijke begeleiders. Hun expertise op het gebied van toegepaste psychologie, wegontwerp en methodologie, samen met hun enthousiasme voor mijn onderwerp, hielpen me de eerste opzet van mijn onderzoek te vormen. Na verschillende discussies begon mijn PhD-reis officieel op 1 januari 2019. Ook al had ik het voorstel voorbereid, het voelde nog steeds als een sprong in het diepe. Van Rijkswaterstaat kreeg ik één dag per week voor mijn onderzoek, en na ongeveer anderhalf jaar kon ik er extra tijd aan besteden, omdat tegen die tijd al mijn kinderen op school zaten. Dit vereiste zorgvuldige planning thuis, en ik ben enorm dankbaar over de afstemming met Marleen zodat ik mijn PhD kon doen terwijl ook Marleen haar ambities als schrijver kon ontplooien.

In mijn initiële onderzoek gebruikte ik op een online enquête als de primaire methodologie. Daarom zou mijn eerste paper niet mogelijk zijn geweest zonder de steun van vrienden en collega's die de enquête actief deelden in hun eigen netwerken. Ik ben me bewust van de toewijding die sommigen van jullie hebben getoond bij het verspreiden en invullen van de enquête, en ik ben oprecht dankbaar voor jullie inspanningen.

Het uitvoeren van mijn on-road studie vereiste aanzienlijke tijd en inspanning van de deelnemers. Ik ben dankbaar voor jullie deelname, vooral omdat het uitdagender bleek dan verwacht om voldoende deelnemers te vinden. Daarom wil ik ook mijn dank uitspreken aan Iris Welvaarts van de ANWB voor het benaderen van ANWB-leden voor deze studie.

Voor het modellering van snelheidsvoorspelling heb ik een aanzienlijke database samengesteld. Dat zou niet mogelijk zijn geweest zonder de financiering van Rijkswaterstaat. Ik wil mijn dank uitspreken aan Jurgen Koppen voor het erkennen van de waarde van deze data bij het verbeteren van ons begrip van snelheid in benaderen van bogen. Ik ben dankbaar voor zijn hulp bij het verkrijgen van de High Frequency Floating Car Data van Be-Mobile, evenals voor de efficiënte re-engineering van de weggedeelten uitgevoerd door Arcadis.

Ik wil speciale dank uitspreken aan het datalab-team van Be-Mobile voor hun ondersteuning bij het starten van het doorgronden van de ruwe data. Ik kreeg de kans om waardevolle tijd door te brengen met Lisa, Jan en Kwinten in Brugge, waarbij ik meer leerde over data-analyse.

In de tweede helft van mijn PhD had ik enkele goede discussies met Ilse Harms. Haar expertise op het gebied van "bekendheid" was waardevol in mijn laatste twee papers.

Gedurende mijn PhD-reis zocht ik feedback bij een klankbord bij Rijkswaterstaat. Alex, Jaap, Raymond en Kirsten, ik wil mijn dank uitspreken voor jullie constructieve input en oprechte interesse. Jullie bijdragen zorgden ervoor dat mijn onderzoek aansloot bij de belangen van Rijkswaterstaat. Bij Rijkswaterstaat deelde ik mijn ideeën, hersenspinsels en besprak ik mijn bevindingen. Enkele van de minder ontwikkelde concepten besprak ik met mijn naaste collega's in het team "geometrisch wegontwerp": Teed, Paul, Hans en Koen. Ik waardeer jullie aandachtig luisteren en praktische feedback. Bovendien deelde ik in verschillende overleggen met betrekking tot bebording, verkeersveiligheid en gedrag inzichten die voortkwamen uit mijn onderzoek. De discussies tijdens en na deze overleggen benadrukten voor mij hoezeer ik de integratie van het toegepast onderzoek waardeer in discussies over het kennisveld van wegontwerp bij Rijkswaterstaat.

Naast de aanzienlijke invloed die mijn paranimfen hadden op mijn onderzoek, waren Jurgen en Chantal van onschatbare waarde bij het assisteren bij de voorbereiding van mijn verdediging. Ik wil mijn oprechte dank uitspreken voor het wegnemen van een deel van mijn stress en voor het etaleren van de grote kennis die we op het gebied van verkeersveiligheid en human factors bij Rijkswaterstaat hebben. Ik hoop nog lang met jullie beiden te mogen samenwerken.

Uiteraard werd de kwaliteit van mijn onderzoek aanzienlijk verbeterd door de begeleiding van mijn promotoren. Marjan en Haneen, ik waardeer de discussies die we hebben gehad; ze waren ter zake kundig en ongelooflijk nuttig bij het organiseren van mijn denkproces. Daarnaast kreeg ik tijdens het bespreken van de on-road studie met Joost de Winter aanzienlijk meer begrip van eye-tracking. Ik ben echt onder de indruk van de hoeveelheid werk die jullie in de academische wereld steken - ik waardeer die inspanningen enorm, maar hoop ook dat jullie goed voor jezelf zorgen!

Mijn ouders probeerden mijn onderzoeksinteresse te begrijpen en lazen mijn papers met bewondering. Hendrik-Jan en Adri, heel erg bedankt voor jullie voortdurende steun gedurende mijn carrière. Jullie hadden het vertrouwen om me mijn eigen pad te laten bewandelen, ook al was het heel anders dan waar jullie aan gewend zijn. Jullie steunden me bij het blijven op de HAVO, de overstap van civiele techniek naar verkeerskunde, het bestuurslid zijn van een faculteitsvereniging op de universiteit en nog veel meer. Bedankt voor jullie geloof in mij.

Deze reis zou echter niet mogelijk zijn geweest zonder de onvoorwaardelijke steun van mijn vrouw. Marleen, ik hou enorm van je en wil je waanzinnig bedanken voor het bieden van tijd en geduld tijdens deze hectische jaren. Ik ben me volledig bewust van de disbalans die mijn PhD in ons gezin heeft gebracht. De Covid-lockdowns testten onze veerkracht, maar ondanks de vermoeidheid slaagden we erin om onze ambities na te streven én tijd vrij te maken voor elkaar en onze kinderen. Niek, Evi en Rosa, jullie hebben gezien hoe ik tijdens de lockdowns in het Engels met mijn begeleiders sprak, en jullie hebben mijn enthousiasme over snelwegen gezien. Ik hou van jullie, jullie nuchtere kijk, knuffels, speelse momenten en nog zo veel meer. Nu is het tijd om thuis weer een balans te vinden en aan onze nieuwe reis te beginnen in ons nieuwe huis - vanuit zoveel perspectieven.

Content

Summary

Although it is known that drivers start to decelerate at a sufficient distance upstream of a sharp freeway curve, it is unknown which cues trigger drivers to start decelerating. Understanding these cues is essential for designing safe roads. Traditional speed prediction models based on geometric curve characteristics have shown significant correlations between curve radius, super-elevation, and operating speed, making them useful for freeway design. However, these models do not consider driver behaviour and have secondary limitations, including biases in data collection, misassumptions about constant speed throughout curves, and a focus on tangent-curve combinations without considering the entire road design.

Safe road design starts with an understanding of the interaction between the driver and the road – i.e., the human factors involved. Human factors research in the context of road design focuses on understanding how the overall road layout influences drivers' behaviour and their performances. Previous studies have explored driver perception, decision-making and behaviour in curve driving, driving tasks categorisation, and the identification risk factors. However, these studies did not provide sufficient quantification of the interaction between the drivers' behaviour and road characteristics to be directly applicable in road design.

General cognitive models, such as the information processing model, recognise the significant role played by memory schemata in information processing. Memory schemata are organised mental templates of expectations and behaviours to help the driver select the correct speed given certain curve characteristics in a mostly unaware process. No research has investigated the specific cues that trigger these schemata for deceleration when approaching a curve, to enhance objectivity and support evidence-based decision-making in road design, it is important to identify the cues used in memory schemata and quantify the relationship between curve characteristics and drivers' speed choices.

The main aim of this dissertation is to quantify the interaction of drivers with road characteristics during curve approach, to be applicable in road design and safety assessments. This entails quantification of the cause-and-effect relation between curve characteristics and drivers' speed choices from a cognitive point of view. The main research question for this dissertation is:

What road characteristics trigger speed adjustments by drivers during curve approach?

Methodology

To answer the main research question, two main approaches were used. Speed prediction modelling to quantify speed behaviour related to curve characteristics, and human factors research to understand and quantify drivers' cognitive processes of the interpretation of curve characteristics during curve approach.

The base conceptual model of this dissertation, shown in Figure 0-1, visualises these two approaches. Arrows labelled "1" relate to speed prediction models connecting curve characteristics to speed behaviour. The human factors approach is labelled "2" along the arrows and assumes causality to understand the relationship between physical reality and human behaviour.

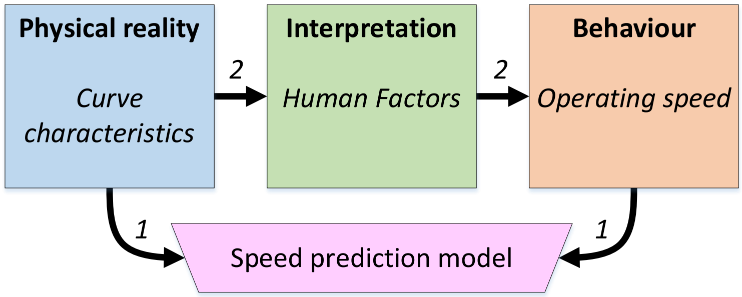


Figure 0-1 The base conceptual model in this dissertation. The connections show the corresponding approaches.

To develop speed prediction models, free flow speed profiles were collected along 153 freeway curves in The Netherlands using High Frequency Floating Car Data. This dataset comprised one million drivers' free-flow speed data, recorded at a frequency of 1Hz. Additionally, various curve characteristics – including discontinuities, sight distances, signs, road geometry, etc. – were added to the database. Correlation and regression analysis were conducted on individual speed profiles to quantify the impact of curve characteristics on the position where drivers start to decelerate and the speed they adhere to in the curve. Next, parsimonious models were generated based on the 85th percentile speeds, to predict the speed development in the vicinity of curves. These models utilise easily obtainable geometric design variables, including the start and end of the horizontal curve, the horizontal radius, and the number of lanes. By using these easily obtainable variables, designers can forecast the speed development relative to the curve's position, based on the 85th percentile of speed and acceleration.

To gain a better understanding of how drivers interact with curve characteristics three studies were conducted. The first study involved an online survey designed to explore which curve cues and other variables influence drivers' speed choice. Eight hundred nineteen participants were presented with 28 sets of curve comparisons, featuring pictures from two different curves from interchanges in the Netherlands. For each set of two pictures, the participants were asked to indicate in which curve they would drive faster. This task aimed to stimulate participants' thought process, leading them to consider the reasons behind their speed preferences. After the 28 comparison tasks, participants were asked to provide their reasons for driving fast in a curve. The curve pictures were then ranked based on the frequency of selection by the participants and compared with their respective curve characteristics. The answers to the open-ended question (i.e., the reasons for driving fast in a curve) were labelled with the curve characteristics that were mentioned and analysed on frequency and clustering of curve characteristics.

The second study was conducted on-road with 31 participants using their own vehicles. The participants drove through six freeway curves while their look ahead fixations and speed were recorded with an eye-tracker and GPS device, respectively. In addition to these measurements, verbalisations of the participants on their speed adjustments were recorded. The distribution of fixations over various areas of interest was analysed relative to the start of deceleration before each curve and relative to the start of each curve. Verbalisation data were analysed to infer the number and types of reasons for changing speed and when these were mentioned together with comments related to deceleration before a curve. This approach results in quantifiable information regarding road characteristics drivers fixate on before adjusting their speed behaviour, which is further explained by the verbalisations given by the participants.

Finally, the third study employs a Bayesian Belief Network (BBN) to model driver expectations regarding safe speed during curve approach using the data collected during the speed prediction modelling. This model mimics expectations as the probability of measured speeds given cues which are visible for drivers, such as the number of lanes or signs. Using Bayes theorem, “prior beliefs” on safe speeds are updated towards a “posterior belief” when a new cue is observed during curve approach. This posterior belief is in the context of this study interpreted as expected safe speed. Drivers are assumed to adjust their operating speed if it does not match their expected safe speed. The developed BBN is employed in two case studies, comparing the modelled expected safe speeds to the operating speed measurements.

Findings

The findings of this dissertation are presented based on two research approaches. Firstly, the results from the speed prediction modelling are presented, followed by the results from the human factors studies.

The results from the speed prediction modelling show significant correlations between the position where drivers initiate deceleration, the speed they maintain in curves, and the horizontal curve radius. Drivers start to decelerate earlier when approaching sharper curves and adopt lower speeds in those. The position where drivers start to decelerate is further explained by sight distances, the number of lanes and the presence of a discontinuity. With the presence of longer sight distances, higher number of lanes, and in the presence of a discontinuity before the curve, drivers start to decelerate later (i.e., closer to the curve start). Higher speed in a curve is further correlated with higher approaching speed, higher number of lanes in the curve, larger deflection angle and the absence of discontinuities in the curve.

The human factors studies in this dissertation show that drivers do not use the horizontal radius to select a safe speed during curve approach. Drivers however rely on other cues to adjust their speed. The online survey conducted identified four common categories of curve cues and variables that influence the decision to drive faster: road environment and surroundings, geometric road characteristics, driver related factors and external influence. The cues related to the road environment and its surroundings were mentioned most frequently by the respondents. The top three variables influencing speed choice are visibility, the overall “overview” of the road (a holistic but difficult-to-measure variable), and the number of lanes. Respondents also frequently mentioned variables such as the presence of signage and trees. Geometric road characteristics like curve radius and deflection angle were recognized by respondents as influencing factors, but their impact on speed selection was observed only when these were visible to the driver and not obstructed by trees or other elements. This suggests that a combination of geometric and surrounding elements is necessary for a better understanding of speed selection by drivers.

The on-road study conducted in this dissertation reveals that before starting to decelerate, the participants primarily fixated on the Focus of Expansion, which is the point on the horizon toward which objects in the visual scene converge when driving in a straight line. They also fixated on edges parallel to the curve trajectory, such as noise barriers, guardrails, or tree lines. Most fixations on warning or speed signs were recorded after participants had already started to decelerate. These findings suggest that drivers primarily use information from the Focus of Expansion, whether it is a change in optical flow (the visual perception of objects’ motion patterns based on their relative positions and movements in the visual field) or the presence of a kink in the alignment, as the main cue to initiate deceleration. Parallel edges also serve as important cues, while warning and speed signs primarily confirm the need for a speed change.

Finally, the Bayesian Belief Network demonstrated that the visible deflection angle of an upcoming curve has a large influence in triggering the expectations of a safe speed. The full deflection angle is not always visible to the driver but can be improved by using parallel edges (or lines) along the curve which are better visible. This increases the detectability of curves’ trajectories because drivers heuristically assume these lines to be parallel to the actual curve. Additionally, the type of roadway preceding the curve and the number of lanes are both important cues for triggering a driver's expectations of a safe speed. Speed and warning signs were found to be interdependent on the road scene and, therefore, have less influence on triggering expectations.

Implications and future research

This dissertation demonstrates the use of two main approaches, namely speed prediction modelling and human factors research, to gain quantifiable insights of the interaction between drivers' behaviour and road characteristics. Through this interaction the driver selects a safe speed given certain curve characteristics. The main conclusion is that while the horizontal radius significantly correlates with speed behaviour during curve approach, drivers primarily use the visible deflection angle, number of lanes and the preceding roadway to adjust their speeds. Speed and warning signs, on the other hand, primarily serve as confirmatory cues rather than being the main factors that influence speed adjustments.

While all used methods combined add to applicable results, especially the application of a Bayesian Belief Network (BBN) shows promising results for future research to quantify driver's unaware reasoning. The BBN approach mimics drivers' expectations as probability distributions and utilises Bayes' theorem to update these expectations when drivers can perceive curve characteristics. However, prior to the development of a BBN, it is essential to identify the cues drivers actually perceive and use. This may require studies such as surveys or eye-tracking experiments to understand which cues drivers rely on. The development of the BBN leads to a quantification of expectations which are assumed to guide the interaction between the drivers' behaviour and road characteristics. By addressing drivers' expectations not only as a qualitative concept, but formulate these in a quantitative way, the BBN becomes a valuable tool in the field of engineering, particularly in designing roads that adhere to the principles of self-explaining roads. It enables engineers to create road designs that align with drivers' expectations and promote safe and intuitive driving experiences.

In addition, "breakpoints" in speed profiles are introduced in this dissertation to identify positions where the deceleration changes. The inclusion of breakpoints offers advantages for studying speed behaviour. It allows researchers to focus on specific segments of the driving task where deceleration changes occur, providing a more detailed analysis of speed adjustments compared to traditional speed prediction models. This approach enables a finer-grained examination of the factors influencing drivers' decision-making during these critical points.

Moreover, aligning these breakpoints with the action component of cognitive models provides an opportunity to partially quantify the interaction between the drivers' behaviour and road characteristics. By identifying the positions where deceleration changes, researchers can align these breakpoints with the corresponding actions (speed change) in cognitive models. This linkage between observed behaviour and cognitive processes provides a valuable means of understanding the underlying mechanisms that drive speed adjustments.

Experiments in controlled environments are still needed to examine the effect of the height of parallel edges – and hence the detection of the total deflection angle – on speed behaviour during curve approach. Furthermore, the analysis presented in the dissertation focuses on curves on main carriageways and connector roads in interchanges. To gain a comprehensive understanding of driver behaviour in freeway curves, extending the research to include curves in on and off ramps (slip roads) is suggested.

Regarding the application of human factor knowledge in road design, the dissertation presents enhancements of existing driving task descriptions for the approach and curve discovery phases and the individual effects of design elements that can aid in analysing existing designs or accident-prone areas. The dissertation emphasizes the importance of incorporating driver perspectives in

road designs and calls for design guidelines that consider the total road environment, including preceding elements and road surroundings. To aid road designers in interpreting these guidelines effectively, the dissertation presents a summarising table displaying permissible combinations of design elements, highlighting combinations that should be avoided.

Samenvatting

Hoewel bekend is dat bestuurders beginnen af te remmen op een voldoende afstand stroomopwaarts van een scherpe bocht op de snelweg, is het onbekend welke signalen bestuurders aanzetten tot decelereren. Het begrijpen van deze signalen is essentieel voor het ontwerpen van veilige wegen. Traditionele snelheid voorspel modellen op basis van geometrische bochtkenmerken hebben significante correlaties aangetoond tussen boogstraal, verkanting en rijsnelheid, waardoor ze nuttig zijn voor snelwegontwerp. Deze modellen houden echter geen rekening met het gedrag van de bestuurder en hebben secundaire beperkingen, waaronder vooroordelen in gegevensverzameling, verkeerde veronderstellingen over constante snelheid in bochten en een focus op combinaties van tangenten en bochten zonder rekening te houden met het hele wegontwerp.

Veilig wegontwerp begint met een begrip van de interactie tussen de bestuurder en de weg, dat wil zeggen de human factors die van invloed zijn. Onderzoek naar human factors in de context van wegontwerp richt zich op het begrijpen van hoe de algehele wegindeling het gedrag en de prestaties van bestuurders beïnvloedt. Eerdere studies hebben bestuurdersperceptie, besluitvorming en gedrag in bocht rijden, rijtaak beschrijvingen en de identificatie van risicofactoren onderzocht. Deze studies hebben echter onvoldoende kwantificering geboden van de interactie tussen het gedrag van de bestuurders en de wegkenmerken om direct toepasbaar te zijn in wegontwerp.

Algemene cognitieve modellen, zoals het informatieverwerkingsmodel, erkennen de belangrijke rol van geheugenschema's in informatieverwerking. Geheugenschema's zijn georganiseerde mentale sjablonen van verwachtingen en gedrag om de bestuurder te helpen de juiste snelheid te kiezen gegeven bepaalde bochtkenmerken in een grotendeels onbewust proces. Er is geen onderzoek verricht naar de specifieke signalen die deze schema's activeren om te gaan decelereren bij het naderen van een bocht. Om objectiviteit te verbeteren en op bewijs gebaseerde besluitvorming in wegontwerp te ondersteunen, is het belangrijk om de signalen in geheugenschema's te identificeren en de relatie tussen bochtkenmerken en de snelheidskeuzes van bestuurders te kwantificeren.

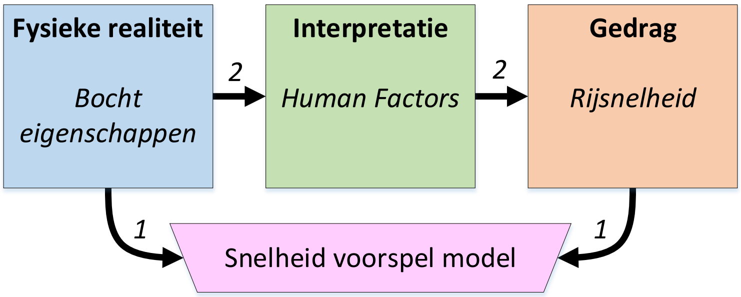
Het belangrijkste doel van dit proefschrift is om de interactie van bestuurders met wegkenmerken tijdens het naderen van een bocht te kwantificeren, zodat deze toepasbaar is in wegontwerp en veiligheidsbeoordelingen. Dit omvat de kwantificering van de oorzaak-en-gevolgrelatie tussen bochtkenmerken en de snelheidskeuzes van bestuurders vanuit cognitief oogpunt. De belangrijkste onderzoeksvraag voor dit proefschrift is:

Welke wegkenmerken zetten bestuurders aan tot snelheidsaanpassingen bij het naderen van een bocht?

Methodologie

Om de belangrijkste onderzoeksvraag te beantwoorden, werden twee hoofdaanpakken gebruikt. Snelheidsvoorspellingsmodellering om snelheidsgedrag in verband met bochtkenmerken te kwantificeren, en onderzoek naar menselijke factoren om de cognitieve processen van bestuurders bij de interpretatie van bochtkenmerken tijdens het naderen van een bocht te begrijpen en kwantificeren.

Het basis conceptuele model van dit proefschrift, weergegeven in Figuur 0-2, visualiseert deze twee benaderingen. Pijlen met label "1" verwijzen naar snelheid voorspel modellen die bochteigenschappen verbinden met snelheidsgedrag. De benadering vanuit human factors is gelabeld met "2" langs de pijlen en maakt gebruik van oorzakelijke verbanden om de relatie tussen de fysieke realiteit en menselijk gedrag te begrijpen.



Figuur 0-2 Het basis conceptuele model in dit proefschrift. De pijlen tonen de overeenkomstige benaderingen.

Om snelheid voorspel modellen te ontwikkelen, werden free flow snelheidsprofielen verzameld langs 153 snelwegbochten in Nederland met behulp van High Frequency Floating Car Data. Deze dataset bestond uit snelheidsgegevens van één miljoen ritten die werden vastgelegd met een frequentie van 1 Hz. Daarnaast werden verschillende bochteigenschappen - waaronder discontinuïteiten, zichtafstanden, borden, weggeometrie, enz. - aan de database toegevoegd. Correlatie- en regressieanalyses werden uitgevoerd op individuele snelheidsprofielen om de impact van bochteigenschappen op de positie waar bestuurders beginnen met decelereren en de snelheid die ze aanhouden in de bocht te kwantificeren. Vervolgens werden eenvoudige modellen gegenereerd op basis van de snelheden van het 85^{e} percentiel, om de snelheidsontwikkeling in de buurt van bochten te voorspellen. Deze modellen maken gebruik van gemakkelijk verkrijgbare geometrische ontwerpvariabelen, waaronder de start- en eindposities van de horizontale bocht, de horizontale straal en het aantal rijstroken. Door gebruik te maken van deze gemakkelijk verkrijgbare variabelen kunnen ontwerpers de snelheidsontwikkeling voorspellen ten opzichte van de positie van de bocht, op basis van de snelheid en acceleratie van het 85^{e} percentiel.

Om een beter inzicht te krijgen in de interactie tussen bestuurders en de weg, werden drie studies uitgevoerd. De eerste studie omvatte een online enquête om te onderzoeken welke bochteigenschappen en andere variabelen van invloed zijn op de snelheidskeuze van bestuurders. Achthonderdnegentien deelnemers kregen 28 sets bochtvergelijkingen voorgelegd, met afbeeldingen van twee verschillende bochten in snelwegknooppunten in Nederland. Voor elke set van twee afbeeldingen werd aan de deelnemers gevraagd in welke bocht ze sneller zouden rijden. Deze taak had als doel het denkproces van de deelnemers te stimuleren, zodat ze de redenen achter hun snelheidsvoorkeuren zouden overwegen. Na de 28 vergelijkingstaken werd aan de deelnemers gevraagd om hun redenen voor het rijden met hoge snelheid in een bocht te geven. Vervolgens werden de bochtafbeeldingen gerangschikt op basis van de frequentie van selectie door de deelnemers en vergeleken met hun respectievelijke bochteigenschappen. De antwoorden op de open vragen (de redenen voor snel rijden in een bocht) werden gelabeld met de genoemde bochteigenschappen en geanalyseerd op frequentie en clustering van eigenschappen in de antwoorden. In de tweede studie werd een praktijkonderzoek uitgevoerd met 31 deelnemers die hun eigen voertuigen gebruikten. De deelnemers reden door zes snelwegbochten terwijl hun oog fixaties en snelheid werden geregistreerd met respectievelijk een eye-tracker en GPS-apparaat. Naast deze metingen werden ook verbalisaties van de deelnemers over hun snelheidsaanpassingen geregistreerd. De verdeling van fixaties over verschillende aandachtsgebieden werd geanalyseerd in relatie tot het begin van deceleratie vóór elke bocht en het begin van elke bocht. De verbalisaties werden geanalyseerd om het aantal en de soorten redenen voor het veranderen van snelheid af te leiden en wanneer deze werden genoemd in relatie tot opmerkingen over vertraging voor een bocht. Deze benadering resulteert in kwantificeerbare informatie over de bochteigenschappen waar bestuurders zich op richten voordat ze hun snelheid aanpassen, die verder worden toegelicht door de verbalisaties van de deelnemers. Ten slotte maakt de derde studie gebruik van een Bayesian Belief Network (BBN) om de verwachtingen van bestuurders met betrekking tot de veilige snelheid tijdens het naderen van een bocht te modelleren, gebruikmakend van de verzamelde gegevens voor de snelheids voorspel modellen. Het BBN bootst verwachtingen na als de waarschijnlijkheid van gemeten snelheden, gegeven de bochteigenschappen die zichtbaar zijn voor bestuurders, zoals het aantal rijstroken of verkeersborden. Met behulp van de Bayesiaanse theorema worden "a priori overtuigingen" over veilige snelheden bijgewerkt naar een "a posteriori overtuiging" wanneer een nieuwe eigenschap wordt waargenomen tijdens het naderen van een bocht. Deze a posteriori overtuiging wordt in de context van dit onderzoek geïnterpreteerd als de verwachte veilige snelheid. Er wordt verondersteld dat bestuurders hun rijsnelheid aanpassen als deze niet overeenkomt met hun verwachte veilige snelheid. Het ontwikkelde BBN wordt gebruikt in twee casestudies, waarbij de gemodelleerde verwachte veilige snelheden worden vergeleken met de gemeten rijsnelheden.

Bevindingen

De bevindingen van dit proefschrift worden gepresenteerd op basis van de twee onderzoek benaderingen. Allereerst worden de resultaten van de snelheids voorspel modellen gepresenteerd. Dit wordt gevolgd door de presentatie van de resultaten van de benadering van de human factors.

De resultaten van de snelheids voorspel modellen laten significante correlaties zien tussen de positie waar bestuurders beginnen met decelereren, de snelheid die ze in bochten handhaven, en de horizontale boogstraal. Bestuurders beginnen eerder te decelereren bij het naderen van scherpere bochten en nemen lagere snelheden aan in deze bochten. De positie waar bestuurders beginnen met decelereren wordt verder verklaard door zichtafstanden, het aantal rijstroken en de aanwezigheid van een discontinuïteit. Met langere zichtafstanden, meer rijstroken en in aanwezigheid van een discontinuïteit beginnen bestuurders later te vertragen (dat wil zeggen, dichter bij het begin van de bocht). Hogere snelheid in een bocht correleert verder met hogere naderingssnelheid, meer rijstroken, grotere booghoek en het ontbreken van discontinuïteit.

Het gedeelte van het onderzoek naar human factors in dit proefschrift laat zien dat bestuurders de horizontale boogstraal niet gebruiken om een veilige snelheid te kiezen tijdens het naderen van een bocht. Bestuurders vertrouwen echter op andere aanwijzingen om hun snelheid aan te passen. De uitgevoerde online enquête identificeerde vier veelvoorkomende categorieën van bocht eigenschappen en variabelen die de beslissing om sneller te rijden beïnvloeden, waarbij die gerelateerd aan de weg en zijn omgeving het meest frequent werden genoemd. De top drie variabelen die van invloed zijn op de snelheidskeuze zijn de zichtbaarheid van bocht, het algemene "overzicht" van de weg (een holistische maar moeilijk meetbare variabele) en het aantal rijstroken. Respondenten noemden ook vaak variabelen zoals de aanwezigheid van bebording en bomen. Geometrische wegkenmerken zoals boogstraal en hoek werden door de respondenten erkend als beïnvloedende factoren, maar hun invloed op de snelheidsselectie werd alleen waargenomen wanneer deze zichtbaar waren voor de bestuurder en niet werden belemmerd door bomen of andere elementen. Dit suggereert dat een combinatie van geometrische en omgevingselementen noodzakelijk is voor een beter begrip van de snelheidsselectie door bestuurders. Het praktijkonderzoek uitgevoerd in dit proefschrift laat zien dat de deelnemers zich vóór het begin van het vertragen voornamelijk richtten op het "Focus of Expansion", dat is het punt aan de horizon waar objecten in het gezichtsveld samenkomen wanneer ze in een rechte lijn rijden. Ze fixeerden ook op randen parallel aan de boog, zoals geluidswallen, geleiderails of bomenrijen. De meeste fixaties op waarschuwings- of snelheidsborden werden geregistreerd nadat de deelnemers al waren begonnen met decelereren. Deze bevindingen suggereren dat bestuurders voornamelijk informatie gebruiken vanuit het "Focus of Expansion", of het nu een verandering in optic flow is (de visuele perceptie van bewegingspatronen van objecten op basis van hun relatieve posities en bewegingen in het gezichtsveld) of de aanwezigheid van een knik in de belijning, als het belangrijkste signaal om het decelereren te starten. Parallelle randen dienen ook als belangrijke aanwijzingen, terwijl waarschuwings- en snelheidsborden voornamelijk bevestigen dat een snelheidsverandering nodig is.

Ten slotte toonde het Bayesian Belief Network aan dat de zichtbare hoek van een naderende bocht een grote invloed heeft op het stellen van de verwachtingen van een veilige snelheid. De volledige hoek is niet altijd zichtbaar voor de bestuurder, maar kan worden verbeterd door het gebruik van parallelle randen (of lijnen) langs de bocht die beter zichtbaar zijn. Dit verhoogt de herkenbaarheid van het bochtverloop, omdat bestuurders heuristisch aannemen dat deze lijnen parallel lopen aan de werkelijke bocht. Daarnaast zijn het type weg voorafgaand aan de bocht en het aantal rijstroken beide belangrijke aanwijzingen voor het stellen van de verwachtingen van een veilige snelheid. Snelheids- en waarschuwingsborden bleken onderling afhankelijk te zijn van de wegomgeving en hebben daardoor minder invloed op het stellen van verwachtingen.

Implicaties en verder onderzoek

Dit proefschrift toont het gebruik van twee hoofdaanpakken, namelijk snelheid voorspel modellering en onderzoek naar human factors, om meetbare inzichten te verkrijgen in de interactie tussen het gedrag van bestuurders en wegkenmerken. Deze interactie leidt er toe dat de bestuurder een veilige snelheid kiest gegeven bepaalde bochtkenmerken. De belangrijkste conclusie is dat hoewel de horizontale straal significant correleert met het snelheidsgedrag tijdens het naderen van een bocht, bestuurders voornamelijk de zichtbare hoek, het aantal rijstroken en de voorafgaande wegindeling gebruiken om hun snelheden aan te passen. Snelheids- en waarschuwingsborden daarentegen dienen voornamelijk als bevestigende signalen in plaats van de belangrijkste factoren die snelheidsaanpassingen beïnvloeden.

Hoewel alle gebruikte methoden bijdragen aan toepasbare resultaten, laat met name de toepassing van een Bayesian Belief Network (BBN) veelbelovende resultaten zien voor toekomstig onderzoek naar de kwantificering van onbewuste redenering van bestuurders. De BBN-aanpak bootst de verwachtingen van bestuurders na als waarschijnlijkheidsverdelingen en maakt gebruik van het Bayesiaanse theorema om deze verwachtingen bij te werken wanneer bestuurders bocht-kenmerken kunnen waarnemen. Echter, voordat een BBN wordt ontwikkeld, is het essentieel om de wegkenmerken te identificeren die bestuurders daadwerkelijk waarnemen en gebruiken. Dit kan studies zoals enquêtes of eye-tracking-experimenten vereisen om te begrijpen op welke signalen bestuurders vertrouwen. De ontwikkeling van de BBN leidt tot een kwantificering van verwachtingen die verondersteld worden de interactie te leiden tussen het gedrag van de bestuurders en wegkenmerken. Door bestuurdersverwachtingen niet alleen als een kwalitatief concept te beschouwen, maar deze kwantitatief te formuleren, wordt de BBN een waardevol instrument op het gebied van wegontwerp, met name bij het ontwerpen van wegen die voldoen aan de principes van "selfexplaining roads". Het stelt ingenieurs in staat om wegontwerpen te creëren die aansluiten bij de verwachtingen van bestuurders en een veilige en intuïtieve rijervaringen bevorderen.

Bovendien worden in dit proefschrift "breakpoints" in snelheidsprofielen geïntroduceerd om posities te identificeren waar de snelheid verandert. De inclusie van breakpoints biedt voordelen voor het bestuderen van snelheidsgedrag. Het stelt onderzoekers in staat zich te concentreren op specifieke segmenten van de rijtaak waar snelheid veranderd, wat een gedetailleerdere analyse van snelheidsaanpassingen mogelijk maakt in vergelijking met traditionele snelheid voorspel modellen. Deze aanpak maakt een betere analyse mogelijk van de factoren die de besluitvorming van bestuurders beïnvloeden tijdens deze kritieke momenten.

Bovendien biedt het afstemmen van deze breakpoints op de actiecomponent (snelheid veranderen) van cognitieve modellen de mogelijkheid om de interactie tussen het gedrag van bestuurders en wegkenmerken gedeeltelijk te kwantificeren. Door de posities waar de vertraging verandert te identificeren, kunnen onderzoekers deze breakpoints afstemmen op de overeenkomstige acties in cognitieve modellen. Deze koppeling tussen waargenomen gedrag en cognitieve processen biedt een waardevol middel om de onderliggende mechanismen die snelheidsaanpassingen activeren, te begrijpen.

Experimenten in gecontroleerde omgevingen zijn nog steeds nodig om het effect van de hoogte van parallelle randen - en dus de detectie van de totale hoek - op snelheidsgedrag tijdens het naderen van een bocht te onderzoeken. Bovendien richtte de analyse in het proefschrift zich op bochten op hoofdbanen en verbindingswegen in knooppunten. Om een alomvattend begrip van bestuurdersgedrag in snelwegbochten te verkrijgen, wordt voorgesteld het onderzoek uit te breiden naar bochten toe- en afritten van snelwegen.

Wat betreft de toepassing van kennis van menselijke factoren in wegontwerp, presenteert het proefschrift aanvullingen van de bestaande beschrijvingen van de rijtaak tijdens de benadering van een bocht, evenals de individuele effecten van ontwerpelementen die kunnen helpen bij het analyseren van bestaande ontwerpen of ongeval gevoelige wegvakken. Het benadrukt het belang van het opnemen van het perspectief van de bestuurder in wegontwerpen en pleit voor ontwerprichtlijnen die de totale wegomgeving, inclusief voorafgaande elementen en de omgeving van de weg, in overweging nemen. Om wegontwerpers te helpen deze richtlijnen effectief te interpreteren, presenteert het proefschrift een samenvattende tabel met toegestane combinaties van ontwerpelementen, waarbij combinaties die vermeden moeten worden, worden benadrukt.

1 Introduction

In 2008, the European Directive 2008/96/EC, known as Road Infrastructure Safety Management ("RISM," 2008), was adopted by the European Parliament and the Council of the European Union. This directive aims to ensure a consistently high level of road safety on the trans-European road network. Subsequently, in 2010, The Netherlands incorporated the RISM into the Public Works Management Act ("Wbr adjustment," 2010), which made it mandatory for all Dutch freeway designs to undergo a Road Safety Audit (RSA).

A RSA is a comprehensive and independent safety check that examines the design characteristics of a road infrastructure project at every stage, from planning to early operation. Its purpose is to identify potential safety issues and critical design elements based on the expected road user behaviour. The introduction of RSA marked a significant advancement in proactive road safety assessment, as it allows for the implementation of road-safety knowledge before accidents occur (Wegman, 2017). Research has shown that this approach effectively reduces the occurrence of actual crashes at a reasonable cost (Sitran, Delhaye, & Uccelli, 2016).

Implementing RSA has led to a greater interest in understanding road user behaviour in relation to road design. Notably, there is a focus on the effects of tight curves on freeways that do not adhere to the designated design speeds, since these curves have a high crash risk (Davidse, Duijvenvoorde, & Louwerse, 2020). Observations have indicated that drivers tend to exceed the design speeds in these curves (Farah, van Beinum, & Daamen, 2017). These factors, along with the increased policy attention to road user behaviour, have motivated the research presented in this dissertation.

This introduction begins by discussing the space requirements and safety considerations of freeway curves, emphasizing the relevant policies in place. The second section focuses on existing scientific literature and identifies the knowledge gaps. In the third section, the aim, scope, and research questions of this dissertation are presented. Section four outlines the methods employed in this research. The fifth section highlights the scientific and practical contributions of this dissertation. Finally, section six provides an outline of the dissertation's structure.

1.1 Space requirements versus safety of freeway curves

Finding the optimum freeway design is a complex process (Casal, Santamarina, & Vázquez-Méndez, 2017), involving many aspects such as traffic demand, safety, environmental issues, cost, etc. Dense physical environments, such as in The Netherlands, require complex design solutions, which are regularly at odds with spatial integration. For example, the increasing urban development usually calls for more on and off ramps on freeways, because of traffic needs. A crucial element in freeway design is the horizontal alignment, consisting of straight segments (tangents), curves and transition curves which connect straight segments with curves (Rijkswaterstaat, 2022). The combination of these elements forms a line through the environment – the horizontal alignment – portraying the position where a carriageway is to be positioned. In dense environments, design solutions usually consist of a large amount of relatively tight curves, reducing spatial requirements and cost. The spatial requirements of a curve are mainly determined by its radius and deflection angle. Figure 1-1 illustrates that when deflection angles are larger, the selection of a radius significantly affects the spatial footprint of a carriageway.

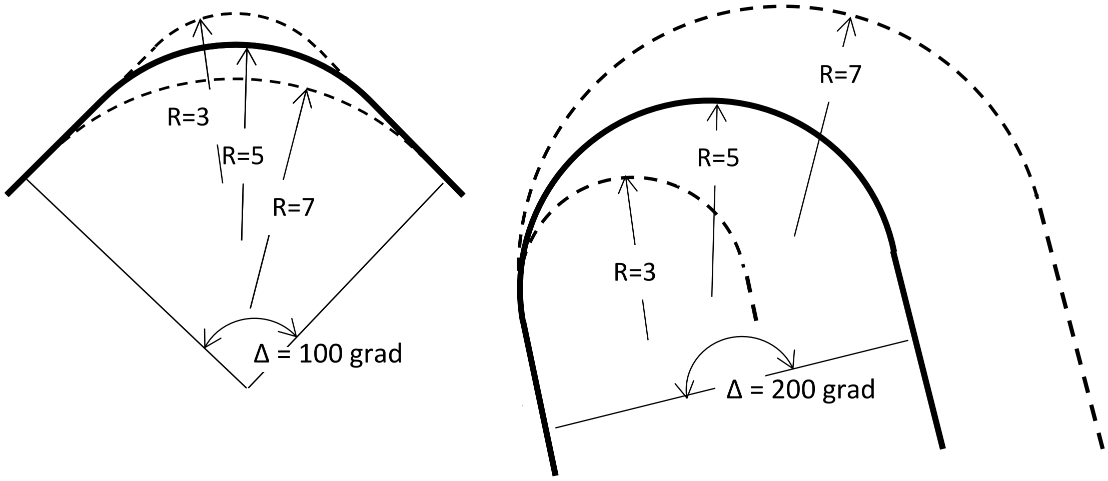


Figure 1-1 The effect of different curve radii (R) and deflection angles (Δ) in the horizontal alignment.

Cheap, space efficient horizontal curves with tight curve radii do however require speed reduction, and are hence known to be unsafe (Davidse et al., 2020). When the curve radius decreases, crash risk increases (Othman, Thomson, & Lannér, 2009; Zegeer, Stewart, Council, & Reinhurt, 1991). A crash is usually caused by drivers who do not expect a sharp curve in a freeway, or overestimate its curvature and hence do not decelerate enough in the curve approach phase (Cafiso & La Cava, 2009). This results in skidding of the vehicle in the curve, because of excessive lateral acceleration in the curve (Peng, Chu, Wang, & Fwa, 2021). A safe road design, viewed from a safe system perspective, takes into account the interactions between vehicle, infrastructure and the driver (Rijkswaterstaat, 2022; SWOV, 2018) as illustrated in Figure 1-2 and elaborated upon by Borsos et al. (2015). The interactions between the vehicle and the road can be labelled as physical factors and mainly refer to skid resistance. How the driver perceives the road and its surroundings and how the driver interacts with the road can be referred to as human factors and is mainly based on applied cognitive psychology. The Dutch safe system approach for improving road safety has human factors as the primary focus (SWOV, 2018). By trying to understand the interaction between the driver and the road, the traffic system can be adapted to achieve maximum safety.

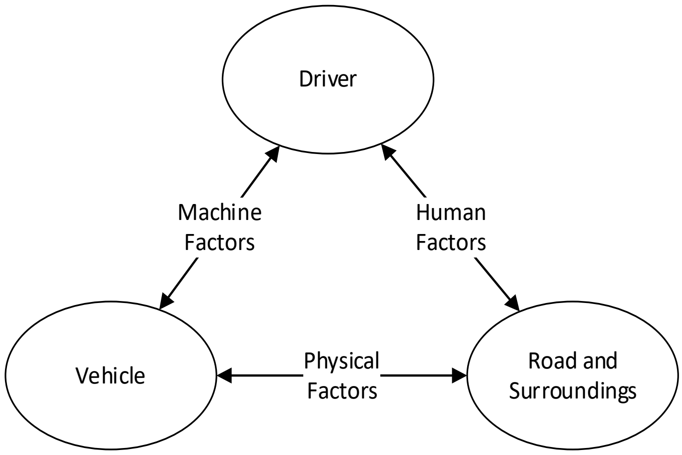


Figure 1-2 The main interactions in the road system, derived from Borsos, Birth, and Vollpracht (2015).

The understanding of how both the driver and the vehicle interact with the freeway, are translated into design guidelines (Rijkswaterstaat, 2022). This translation is generally done by providing applicable formulas, or standardised measurements in tables which reflect best practices. This quantification of knowledge helps roads designers in making informed design decisions. However, the background of the current Dutch guidelines for safe curve design are based on research from the 1970s (Brevoort, 1974; Cate, 1974; Pacejka, 1974) which focusses on the relation of the vehicle and the road – the physical factors. Since then, the design guidelines have been updated to reflect the latest best practices and a better understanding of curve geometry. This took into account various factors like different types of pavements, vehicle dynamics, and driver expectations. These updates, however, were not properly documented, so the guidelines cannot be benchmarked to evidence-based research anymore. Therefore, designers and auditors have problems motivating deviations from the guidelines. Especially since more complex design solutions call for tighter curve radii, a re-evaluation of the interaction of drivers and vehicles with curves is needed. The first step of this process is the interaction of the driver with the road and its environment during curve approach and the driver's decision to start decelerating to proceed with a safe speed. Understanding how the driver makes this decision is therefore essential to create a safe road design. This dissertation focusses on the interaction of the driver with the road and its environment – i.e. the human factors. In order to make this knowledge accessible in freeway design, quantification of this interaction between the drivers' behaviour and road characteristics is needed. The quantifications in this dissertation are related to the road characteristics drivers indicate to be important for speed adjustments during curve approach, correlation between deceleration and road characteristics, look ahead fixation duration during curve approach and the unaware expectations drivers have built on safe speeds in curves given certain observed curve characteristics. Using such quantifications, designers can make more objective, evidence-based design decisions. This enables them to compare different designs and ensure that road designs are optimised for driver performance and safety.

1.2 Literature review and knowledge gap

Design of freeway curves is usually based on design speed (Fitzpatrick & Kahl, 1992; *A Policy on Geometric Design of Highways and Streets 2018*, 2018; Rijkswaterstaat, 2022) which is a selected speed used to determine the various geometric design elements of the carriageway (Porter, Donnell, & Mason, 2012). Design speeds use physical forces in point mass models (Donnell, Wood, Himes, & Torbic, 2016) to tie speed and curve radius together in a simplified representation of a vehicle as a single point travelling through a curve. This results in design speeds that are a function of super-elevation and curve radius in order to reduce risk of skidding and offer a comfortable ride at these design speeds. These design speeds are hence mainly based on physical models of the forces between the vehicle, the infrastructure, and the driver. Design speed is therefore an important factor in setting road design parameters. This importance is reinforced by the understanding that excessive speeds are the main cause for accidents in curves (Aarts & Van Schagen, 2006; Domenichini, Paliotto, Meocci, & Branzi, 2022). This literature review first focusses on the correlation between operating speed and curve characteristics, which are covered in speed prediction models (section 1.2.1). Speed prediction models, however, typically do not include the driver's interaction with the road, generally referred to as human factors. So, following speed prediction models, human factors are introduced in section 1.2.2 by discussing task descriptions, risk and cognitive process models, and relevant empirical studies of curve perception. After reviewing relevant literature in both approaches (speed prediction and human factors), the knowledge gaps are identified that this PhD research aims to address.

1.2.1 Speed prediction models

Measuring operating speeds and relating these to geometric curve characteristics leads to speed prediction models (Hassan, Sarhan, Porter, et al., 2011; Odhams & Cole, 2004; Shallam & Ahmed, 2016). These models show significant correlations between curve radius, super-elevation and operating speed, resembling the way design speed is modelled. These models are great in quantifying speed behaviour related to curve characteristics and making these relations accessible for freeway design.

However, existing speed predicting models have severe deficiencies, which are discussed by Hassan, Sarhan, and Dimaiuta (2011). They identified different biases regarding data collection and the assumptions underneath the development of these models. Regarding data collection the selected road segments need to be carefully picked to avoid biases resulting from influences of upstream road elements such as nearby intersections. Next to that, the chosen speed collection methods can bias the results because of limited sample sizes and number of observations, as well as errors in manual speed measurements. A major misassumption in traditional models is that speed is constant throughout a curve. More recent studies using naturalistic driving data have shown that speed throughout a curve varies (Cafiso & Cerni, 2012; Dias et al., 2018). Traditional speed prediction models, using a single measurement for operating speed in a curve, which usually was taken at the centre of a curve, therefore giving an unrealistic representation of actual human speed behaviour. Studies using continuous speed profiles provide a better understanding of speed development, including acceleration and deceleration. These speed profiles show how deceleration starts before the curve and ends in the curve (Montella, Galante, Imbriani, Mauriello, & Pernetti, 2014). Another assumption in traditional speed prediction models is that speed measures from the curve are independent from upstream and downstream road sections, while both upstream and downstream elements influence operating speed (Hassan et al., 2011).

Moreover, it has been identified that most models focus on tangent-curve combinations, without considering the entire road design (upstream and downstream horizontal and vertical elements, type of discontinuity and (changes in) cross section and its environment (Cafiso & Cerni, 2012). The specific road design elements of influence are not mentioned in these studies though.

Most speed prediction models use the horizontal radius of a curve as the main independent variable to explain the operating speed in the curve (Hassan, Sarhan, Porter, et al., 2011). Recent speed prediction models show that the operating speeds in the Netherlands are well above the design speeds (Farah et al., 2017), so design speeds are not similar to operating speeds. Therefore, the measured operating speeds cannot be explained using traditional design speed approaches. After all, drivers do not drive through a technical and theoretical design, but through a real-life freeway environment. This calls for taking driver behaviour also into account when analysing operating speeds.

1.2.2 Human factors

Driver behaviour is primarily based on the perception of the driver, since "*it is the perceived situation not the physical reality that determines behaviour*" (Rumar, 1982). Human factors research in road design involves studying the interactions between the driver and the road and its environment to understand human capabilities, limitations, and behaviour. A wide variety of factors is believed to influence drivers speed choice (e.g., road and vehicle factors, traffic and environment factors, driver related factors). Various behavioural models have been designed to help understand how drivers function and choose their speeds. But it is recognised that no comprehensive model of driving behaviour exists, nor is there a standard categorisation of models (Ranney, 1994; Shinar, 2017b). In this overview, relevant models are divided into two categories: describing what the driver does (task descriptions and errors), and why and how the driver does this (risk and cognitive process models). After an overview of these models, relevant human factors studies of curve driving are discussed.

1.2.2.1 *Task descriptions and errors*

Task descriptions serve to analyse the driving task in specific situations and create specific task requirements. Driving task descriptions (Campbell et al., 2012; McKnight & Adams, 1970) provide insights into the different phases during curve driving: curve not yet in sight (anticipation), curve in sight (discovery), within a curve (negotiation) and exiting a curve (leaving). These zones need different driving tasks. For the determination of safe speeds, speed signs and curve radius are mentioned as primary indicators. In the discovery phase of curve driving, speed is adapted to a suitable speed based on curve cues, which are not further defined in the task description. Within the curve the speed is adjusted to the actual curvature and lateral acceleration.

On a more general level, driving tasks can be categorized into three hierarchical task levels: strategic (planning), tactical (manoeuvring) and operational (control) (Michon, 1985). Curve driving is generally assumed to be done at an operational level, since it is mainly a subconscious driving task. These three levels match up with the classification of human behaviour by Rasmussen (1982), who distinguishes three levels: skill-, rule- and knowledge-based behaviour. Skill-based behaviour relies on accumulated experience that has been stored in memory and manifests as largely automated behaviour. Rule-based behaviour acts on known rules and familiar situations, and is regarded as more conscious behaviour. Knowledge-based behaviour, while also conscious, involves using current knowledge in unfamiliar situations where limited prior experience is available.

Speed selection in curves is considered a skill-based process (Ranney, 1994) that operates without active thinking while driving, as it relies on automated routines developed through experience. At this level, errors can occur when drivers do not perform the appropriate attentional control over their actions, leading to the activation of incorrect routines (Reason, 1990). These errors may arise due to insufficient attention given to the curve cues, or misinterpretation of curve cues, resulting in the selection of an inappropriate speed. Skill-based activities can lead to unintended actions defined as slips (correct intention or plan, but the execution fails) or lapses (failure to perform an intended action or forgetting the next action in a sequence). In curve driving, these errors can result in skidding or running off the road.

1.2.2.2 *Risk models*

Risk is widely recognized as a key motivational component for drivers. One of the most influential theories in this regard is the risk homeostasis theory proposed by Wilde (1998), which states that drivers accept a certain level of risk in exchange for the benefits they gain. This implies that drivers make a trade-off between a certain risk of skidding in curves and time saved by driving at higher speeds.

In order to maintain their safety margins, drivers are thought to utilise comfort zones, which help them avoid crossing certain thresholds (Summala, 2007). Drivers’ automatic and unconscious behaviour, shaped by their experience, allows drivers to adhere to specific safety margins they have learned over time. These safety margins keep drivers within a pleasant comfort zone and influence their decision-making regarding driving speeds (Van Winsum & Godthelp, 1996). Higher speeds in curves create higher lateral acceleration, which is known to decrease comfort levels (Dhahir & Hassan, 2019b). When drivers exceed their comfort zone by choosing higher speeds for the sake of time savings, they experience uncomfortable feelings that can serve as safety warnings. These comfort zones align closely with the safety zones defined by Gibson and Crooks (1938), who already in 1938 theorised that drivers respect safety zones by decreasing their speed to prevent skidding or running off the road. They defined a “field of safe travel” based on factors such as acceleration, deceleration, and a minimum stopping zone. Their theory is in essence an information processing model based on the perception of safety zones and the subsequent reaction of the driver by steering or decelerating.

1.2.2.3 *Cognitive process models*

Information processing or cognitive process models outline the mental processes and typically consist of three basic steps: perception, decision making and action. Memory plays a pivotal role in information processing as it involves encoding, storing, and retrieving information. This is shown in Figure 1-3, which presents a model of human information processing adapted from Wickens, Helton, Hollands, and Banbury (2021) and Endsley (1995). The model begins with sensory processing such as the processing that occurs on the retina of the eye. While this dissertation does not delve into the specifics of sensory processing, it is important to note that it leads to the subsequent process of perception.

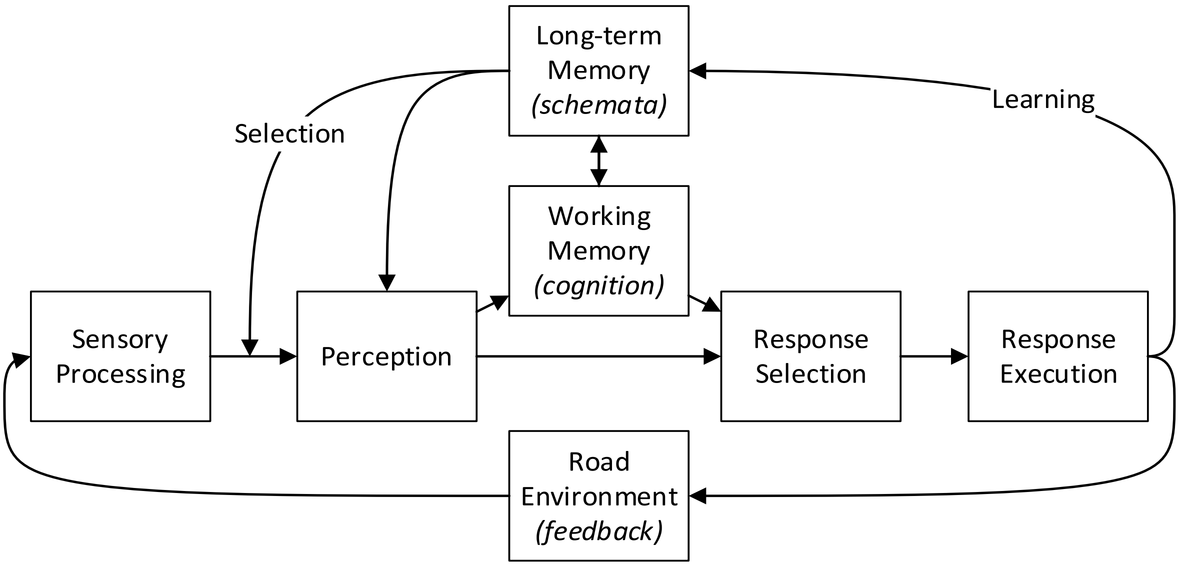


Figure 1-3 A model of human information processing.

Perception itself is the process of becoming aware – on different levels – of the world around us (Shinar, 2017b). The driving task specifically, is predominantly fed by visual perception (Sivak, 1996). Cognitive models often incorporate Neisser's perceptual cycle (Neisser, 1976) to explain the perception component. This cycle involves continuous interaction with the environment, using cues and schemata stored in long-term memory. Positioned between perception and action (i.e., response execution), is cognition, where working memory combines perception and the stored schemata to interpret the perceived information.

Schemata can be considered as organised mental patterns of thoughts or behaviours to help organise world knowledge (Neisser, 1976). They are based on multiple experiences and associations, providing a generalised and adaptable framework without much detail (Ghosh & Gilboa, 2014). Schemata help the driver optimize their behaviour and make quick decisions based on expectations stored in memory as schemata. They affect how drivers perceive information about the (road)environment and how this information is being activated (Plant & Stanton, 2012). Schemata assist in selecting appropriate speed based on perceptual cues (Charlton & Starkey, 2017a, 2017b; Ranney, 1994), leading to automatic performance characterised as efficient, unintentional, and unconscious behaviour (Charlton & Starkey, 2011). Errors occur when incorrect schemata are activated, leading to the selection of inappropriate responses. In this dissertation, a schema will be considered as an organised mental template of expectations and behaviours to help the driver select the correct speed given certain curve characteristics in a mostly unaware process.

The principles of dual process theory (Evans, 2003; Kahneman, 2011) shed light on driving without awareness (Burdett, Charlton, & Starkey, 2019; Charlton & Starkey, 2011, 2018a, 2018b; Malhotra, Charlton, Starkey, & Masters, 2018) which is associated with rapid and automatic thinking (Evans, 2003). This aligns with bottom-up driving (Charlton & Starkey, 2011), which is composed of wellrehearsed perception-action units allowing experienced drivers navigate traffic with little or no conscious attention. Existing theories are mostly based on descriptions of the conscious, top-down driving mode (Charlton & Starkey, 2011), hence they pose a challenge when considering driver behaviour in curve driving.

Driver behaviour is not simply a dichotomy between top-down vs bottom-up. Charlton and Starkey (2011) propose a tandem-like approach in which both systems constantly work together and depend on each other. In visual awareness research it is still discussed whether this is dichotomous or graded (Windey, Vermeiren, Atas, & Cleeremans, 2014). However, it is agreed that easy, well-known stimuli get processed bottom-up, leading to partial awareness (Fazekas & Overgaard, 2018).

Unawareness is also common in driving, as drivers are prone to mind-wandering, even while successfully executing correct motor responses (Burdett et al., 2019). Neurological research suggests different pathways from the retina that lead to either perceptual awareness or motor output during early visual processing (Lamme, 2018; Spering & Carrasco, 2015).

1.2.2.4 Human factors studies of curve driving

Visual perception plays a pivotal role in the driving task (Sivak, 1996), prompting researchers to investigate how drivers perceive curves. In the early years of this research, perspective drawings were primarily employed. But over the years, the utilization of eye tracking, driving simulators and surveys became prevalent in experimental settings. More recently, naturalistic driving studies and instrumented vehicles have emerged as additional methodologies in this field of research. These advancements have allowed for a deeper understanding of how drivers perceive curves, which are discussed below.

Perspective drawings revealed significant disparities between the visual image of a curve and its physical properties (Bakker & Springer, 1961; Springer, Huizenga, & Moonen, 1970). These studies showed how curves are predominantly perceived as hyperbola by the driver. Perspective drawings also emphasised the significance of curve angle (Fildes & Triggs, 1985; Riemersma, 1988) and the possible distortion of the curve perception caused by transition curves (Riemersma, 1989). Early eye tracking experiments identified the “tangent point” (the point on the inside of a curve, where the apparent curvature of the curve reverses) as a focus point for drivers while navigating through a curve. It was found that drivers begin searching for this point approximately 1 to 2 seconds before a curve (Land & Lee, 1994; Shinar, McDowell, & Rockwell, 1977).

Subsequent eye tracking studies showed that drivers also seek information outside the “tangent point” about the trajectory of a curve (Lappi & Lehtonen, 2013; Lehtonen, Lappi, & Summala, 2012), based on driving experience (Lehtonen, Lappi, Koirikivi, & Summala, 2014; Tuhkanen et al., 2019). Driving simulator experiments have been used to validate theories such as the “two point” steering model (Jamson, Benetou, & Tate, 2015; Salvucci & Gray, 2004), which suggests that drivers use a near and a far focus point to guide their steering during driving. Additionally, the importance of curve radii and lane width in speed selection was also confirmed through simulator studies (Bobermin, Silva, & Ferreira, 2021; A. Calvi, 2015; Van Winsum & Godthelp, 1996). Both driving simulators and naturalistic driving experiments demonstrated that more experience (driving experience in general, and knowledge about specific curves) lead to higher speeds (Charlton & Starkey, 2011; Pratt, Geedipally, Dadashova, Wu, & Shirazi, 2019), and hence higher risk acceptance.

Surveys help understand driver risk acceptance (Deng, Chu, Wu, He, & Cui, 2018; Xie, Wu, Lyu, & Duan, 2019), by showing the influence of driving style and workload on speed behaviour. Surveys, when combined with other research methodologies, have added value to experiments in giving more qualitative meaning to the quantitative results.

Such human factors studies in curve driving have given valuable observations into the variables which play an important role in curve negotiation and speed selection. Most of these studies, however, do not give a generalizable and quantifiable knowledge into speed selection, making it challenging to directly apply them in road design processes.

1.2.3 Knowledge gap

Existing knowledge regarding speed prediction models and driver behaviour indicates a gap between the "real world" and its representation and interpretation by the driver. This discrepancy has been attributed to the behaviouristic approach in understanding driver behaviour prevalent in the 20th century (Michon, 1985). *Behaviourism* focusses on the correlation between visual input – i.e., curve characteristics – and observable behavioural output – i.e., speed – without considering the underlying mental processes of the driver. In contrast, *cognitivism* takes a more comprehensive approach by considering how visual input is interpreted and translated into observable output, as shown in Figure 1-3, thereby establishing a causal relationship. While behaviourism has contributed to describing driving tasks and developing speed models, cognitivism provides a deeper understanding of the underlying processes involved.

Within the field of applied cognitive psychology, that focusses on studying the basic aspects of human perception and cognitive processes relevant to human behaviour, it has been identified that it remains unknown which specific schema or mental template is activated in different road environments (Salmon, Lenne, Walker, Stanton, & Filtness, 2014). To the best of our knowledge there is no research on the cues that trigger specific schemata drivers use to determine their speed. This gap exists because most human factors studies on curve driving concentrate on the curve itself, not on the approach part where deceleration is known to start. Therefore, in this dissertation, it is assumed that the cues activating specific schemata for speed deceleration are visible during the approach to the curve, rather than in the curve itself.

It should be noted that most theories on driver behaviour are based on descriptions of the conscious, top-down driving mode (Charlton & Starkey, 2011) which involves conscious, deliberate effort of the driver. Speed selection and curve driving are however considered bottom-up cognitive processes (Ranney, 1994) with little or no conscious attention or effort by the driver, which are based on expectations stored in schemata.

Therefore, the main knowledge gap lies in *understanding the specific cues that trigger schemata for deceleration during the approach of a curve*, as most existing research focusses on the curve itself and fails to address the bottom-up cognitive processes involved in curve driving with little conscious attention or effort from the driver.

1.3 Aim and research questions

The topic of this dissertation is the interaction between the drivers' behaviour and road characteristics during curve approach. The aim is to quantify this interaction, connecting speed adjustments to road characteristics and driver behaviour such as eye fixations and development of expectations. This research is essential because most existing human factors studies lack comprehensive and quantifiable insights into speed selection.

Quantification is crucial for applying knowledge about driver behaviour to road design and improving safety assessment methods. To achieve this goal, a diverse range of data is collected, covering both curve characteristics and driver behaviours. These data form the basis for quantifying and analysing the driver-road interaction from the perspective of the driver.

By examining the three basic steps of human information processing (perception, decision making, and action), a better understanding of drivers' cognitive processes during curve approach can be achieved. Speed selection is assumed to be driven by expectations which are stored in schemata, connecting specific road characteristics to specific speed adjustments. As drivers start to slow down prior to entering a curve, these schemata are expectations built upon road environment upstream of a curve. This results in the following main research question:

What road characteristics trigger speed adjustments by drivers during curve approach?

Schemata, which are assumed to be mental representations, cannot be directly measured (Walker, Stanton, & Salmon, 2011). Therefore, this dissertation employs two approaches identified in the literature review for this purpose: speed prediction modelling and human factors analysis. Consequently, two complementary research questions will provide quantifiable observations into curve approach behaviour related to curve characteristics. Research question 1 is as follows:

1. What road characteristics are correlated to speed behaviour during curve approach?

Identifying these correlations helps to quantify the effect of different road characteristics on speed adjustments. These correlations can be quantified using speed, deceleration at specific positions during curve approach, and curve characteristics. However, correlations do not identify causation because they merely indicate relationships between variables, while schemata are temporal in nature employing a cause-and-effect relationship. This cause-and-effect structure relates to driver's information processing. The "cause" part represents a specific road characteristic that the driver perceives, triggering the activation of the relevant schema. The "effect" part represents the expected speed adjustments based on the activated schema. This temporal nature of schemata highlights the importance of understanding the utilization of road characteristics in drivers' information processing. Therefore, research question 2 is as follows:

2. What road characteristics are utilized in drivers' information processing and speed adjustment decisions during curve approach?

This question delves into the causal relationship between road characteristics and their utilisation in drivers' information processing during curve approach. By investigating how drivers incorporate specific road features into their decision-making processes, the study can identify the relevant road characteristics that play a role in the formation and activation of memory schemata. Understanding the utilization of road characteristics in drivers' information processing helps to understand the causal connections between these features and speed adjustments stored in drivers' memory schemata.

By addressing both research questions, the dissertation can quantitatively examine the correlations between road characteristics and speed adjustments, while also investigating the causal relationships and utilization of these characteristics in the drivers' information processing. Together, these research questions provide a comprehensive understanding of the road characteristics which trigger speed adjustments during curve approach. The following paragraph discusses the methods used to answer these research questions.

1.4 Methods

To guide the research questions and methodologies a base conceptual model has been developed. Figure 1-4 shows this model, incorporating the elements of both speed prediction modelling and human information processing. On the left the physical reality (curve characteristics) is represented. On the right-side driver behaviour (operating speed) is captured. In the middle, the interpretation of the driver is defined as human factors, which reflects the interaction between the road and the driver. This provides a concise summary of the information processing model shown in Figure 1-3. The arrows show the direction of information processing is temporal, aligning with research question 2 and provides and understanding about *why* drivers start to decelerate.

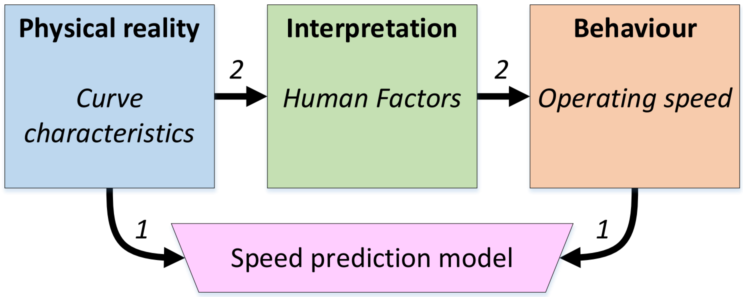


Figure 1-4 The base conceptual model in this dissertation. The connections show the corresponding research question.

Below the human factors process, there is a box representing speed prediction modelling. The arrows show that this modelling takes the input from both the physical reality (curve characteristics) and the driver behaviour (speed adjustment). This modelling approach is used to address research question 1 aiming to identify the correlations between road characteristics and observed speed behaviour. This provides understanding about *what* behaviour occurs. The following paragraphs discuss the methods used in both approaches, and how they can be combined to provide a comprehensive understanding of the main research question.

1.4.1 Speed prediction modelling

The relationship between the physical world and operating speeds can be modelled objectively using speed prediction models. In this dissertation *free-flow speed profiles* are analysed in relation to the *curve characteristics* during curve approach. The physical reality is translated in a comprehensive set of variables which are analysed on *correlation* and *regression* with the individual speed profiles to answer research question 1.

To ensure practical applicability in early design phases, the dissertation also creates *parsimonious models*. These models capture the speed development using the fewest possible variables. By minimizing the number of variables required to accurately model speed development, these parsimonious models offer practical utility and enhance their usability in early design considerations.

1.4.2 Human factors approach

Since no specific literature is available on the cues drivers use during curve approach, an *online survey* is used to understand the factors influencing drivers speed selection. Because existing literature suggests that the interaction of the driver with the road is primarily visual (Sivak, 1996), also an *on-road study* is conducted using *eye-tracking* to unravel the specific cues that participants fixate on during curve approach. Additionally, the participants engaged in *speaking aloud* procedures which allowed for a qualitative understanding of the quantified relations between eye fixations and speed during curve approach.

Furthermore, literature shows that most of the deceleration behaviour is unaware, based on expectations stored in schemata. To model these driver expectations, a *Bayesian Belief Network*

(BBN) is employed which is assumed to mimic driver expectations. This method utilises probability distributions of curve characteristics and speed distributions gathered during the speed prediction modelling. By incorporating these distributions, the BBN provides a framework to capture the updating of driver speed expectations during curve approach.

Together, the online survey, on-road study, and Bayesian Belief Network contribute to a better understanding of the cues that drivers utilise, the unconscious expectations they hold, and the cognitive mechanisms involved in speed selection during curve approach.

1.4.3 Combining the approaches

The answers to research question 1 explain *what* behaviour occurs. The answers to research question 2 delve deeper into the underlying reasons *why* these behaviours manifest, utilizing the model of human information processing shown in Figure 1-3. By combining both approaches, the answers to the research questions contribute to a quantifiable understanding of human factors and provide further explanation for the operating speeds observed during curve approach.

To our knowledge, no previous research has explored the combination between speed prediction and human factors in the context of driver behaviour during curve approach. Therefore, the aim of this dissertation is to establish a first integration between these two research approaches. This process is discussed in the conclusions of this dissertation, highlighting the significance of this novel integration, and suggesting avenues for future research.

1.5 Contributions

Literature on cognitive processes identifies that it is a challenge to uncover mental processes (Walker et al., 2011), specifically related to how drivers construct schemata of the environment to adjust their speed (Charlton & Starkey, 2017b; Salmon et al., 2014). This dissertation employs mixed methods to help understand and quantify the interaction between the drivers' speed behaviour and the road characteristics during curve approach.

The quantitative research uses breakpoints in speed profiles as key variables. Building upon the initial work by Montella, Galante, Mauriello, and Aria (2015) in a simulator experiment, this dissertation enhances the use of breakpoints to examine naturalistic, free-flow speed profiles. Breakpoints identify the positions where drivers start and stop their deceleration and can therefore act as identifiers of the position where drivers initiate action. This approach shows prospects for future research in speed adjustments, providing a better understanding of driver speed behaviour. While this approach was primarily employed in the analysis of speed profiles based on High Frequency Floating Car Data, it was also used in an on-road study, combining it with eye-tracking and speaking aloud methods. This unique combination of methods for data collection provides a temporal understanding of human cognitive processing during curve approach, allowing for a better understanding of drivers' curve approach behaviour.

The qualitative research uses mostly feedback from drivers, both in an online survey and during the on-road study. This active feedback on the reasons why drivers change their speed, helps to better explain the quantitative results and to select the relevant road characteristics drivers use during curve approach, which is usually overlooked in traditional speed prediction modelling.

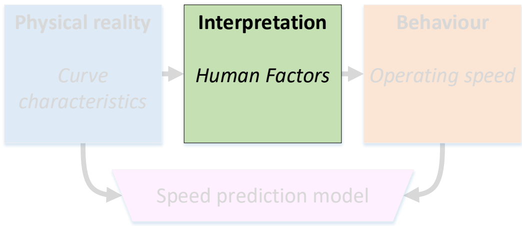
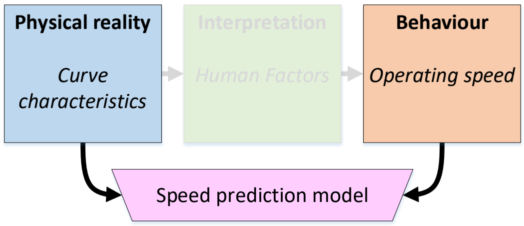
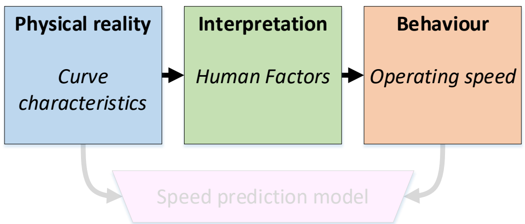
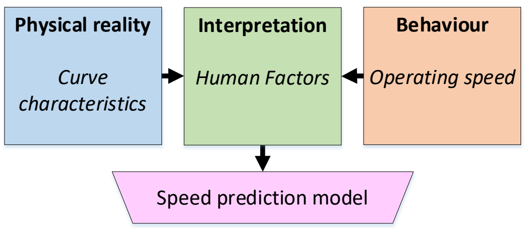
The knowledge of which road characteristics are relevant for drivers, was used to build a Bayesian Belief Network (BBN) to mimic drivers' expectations of safe speeds during curve approach and quantify the importance of these road characteristics. While Bayesian approaches have gained popularity in neuropsychology (Geurts, Cooke, van Bergen, & Jehee, 2022; Wilder, Feldman, & Singh, 2016), their use in applied cognitive psychology is relative new and have – to our knowledge – not been applied in traffic psychology. This dissertation explored the use of a BBN to understand driver's expectations, aligning with the concept of self-explaining roads (Theeuwes, 2021).

The findings of this research can be used to update the Dutch design guidelines on freeway geometry (Rijkswaterstaat, 2022). This is expected to lead to freeway design that takes into account the driver's perspective. Furthermore, traffic safety auditors can use the results to broaden their knowledge base and they have improved tools available to evaluate new designs and existing freeways. This includes parsimonious speed prediction models, identification of important design elements for drivers, an enhancement of existing driving task descriptions for the approach and curve discovery phases and an evidence-based design guideline table displaying permissible combinations of design elements, highlighting combinations that should be avoided.

1.6 Outline

This dissertation is structured into five main chapters each addressing different aspects of the research questions. The main chapters are outlined in Table 1-1, showing which elements in the conceptual model are discussed in the chapters, and how these elements are connected.

Table 1-1 Main outline of this dissertation.

Chapter	Content	Elements in conceptual model
2	The second chapter explores which curve cues and other variables influence drivers' speed choice in curves using an *online survey*. It therefore aims to gain mainly qualitative understanding in drivers' interpretation of curve characteristics. These variables are further explored in the following chapters.	
3	The third chapter identifies the correlation between freeway characteristics identified in chapter 2 and deceleration upon curve approach. To do so, curve characteristics from 153 curves and 1 million *individual, free-flow speed profiles* are analysed. This is essentially speed prediction modelling based on individually measured speed behaviour.	
4	The fourth chapter generates *parsimonious models* to predict speed development based on 85th percentile speeds, including deceleration and acceleration behaviour upon entering and exiting freeway curves. The models rely on easy to generate geometric design variables, providing a practical approach to speed prediction.	
5	The fifth chapter helps understand the perceptual and cognitive processes of drivers during curve approach. Through an *on-road study* using eye-tracking, GPS tracking, and verbal protocol analysis, the visual cues that drivers use before and during deceleration are identified. It aims to gain causal insights in the correlations identified in chapters 3 and 4.	
6	The sixth chapter combines the gained quantitative data and qualitative knowledge from the previous chapters and generates a *Bayesian Belief Network* to model driver expectations during curve approach. This approach does not rely on correlation between curve characteristics and operating speed to model behaviour, but it mimics the interpretation of the curve characteristics and speed behaviour to capture driver behaviour.	

The final chapter summarizes and discusses the outcomes from the speed prediction modelling and human factors approach, addressing the two research questions and providing an understanding of the cues that drivers use, thereby answering the main research question. In addition, it provides recommendations for future research and policy implications regarding design guidelines.

2 A Survey to Explore Which Variables Drivers Say They Use in Curve Approach

This chapter has previously been published as: ***Vos, J.**, Farah, H., & Hagenzieker, M. (2021). How do Dutch drivers perceive horizontal curves on freeway interchanges and which cues influence their speed choice? IATSS Research, 45*(2), 258-266.

Abstract

Operating speeds in Dutch freeway curves differ often by 20 km/h compared to their design speeds. Operating speed is thought to be influenced by how drivers perceive curves their speed choice when approaching a curve. This explorative research explores which curve cues and other variables influence drivers' speed choice in curves. For this purpose, a survey was designed with 28 sets of curve comparisons. The curves were chosen from interchanges in the Netherlands and were compared to each other. To avoid direction bias, the curves were right turning only. In each set illustrations of two different curves out of a total of 8 curves were shown, and the participants were asked in which curve they would drive faster. In total 819 participants in the age range of 18 and 78 (mean=41.3; Std.=11.9) completed the survey. The survey data showed four common categories of curve cues and variables influencing the decision to drive faster, of which those in the category of the road environment and its surroundings were mentioned the most. The top three variables influencing speed choice are visibility of curve characteristics, "overview" as a holistic but as such hard to measure variable, and number of lanes. Variables such as presence of signage and trees were also mentioned frequently by the respondents. Geometric road characteristics such as curve radius and deflection angle were identified by the respondents as influencing variables, but only showing to affect speed selection when these are visible to the driver and not obscured by trees or other elements. This suggests combinations of geometric and surrounding elements are needed to get a better understanding of speed selection by drivers.

2.1 Introduction

Design of freeway curves is usually based on design speeds (Fitzpatrick & Kahl, 1992; *A Policy on Geometric Design of Highways and Streets 2018*, 2018; Rijkswaterstaat, 2022) which use physical forces in point mass models (Donnell et al., 2016) to tie speed and curve radius together. This results in design speeds that are a function of superelevation and radius, in order to reduce the risk of skidding and offer a comfortable ride. These design speeds are therefore mainly based on physical models of the forces between the infrastructure and the vehicle through skid resistance, and between infrastructure and the driver through comfort coefficients. There is, however, a difference between design speed and operating speed.

Measuring operating speeds and connecting these to geometric curve characteristics lead to speed prediction models (Hassan, Sarhan, Porter, et al., 2011; Odhams & Cole, 2004; Shallam & Ahmed, 2016). These show significant correlations between curve radius, superelevation and operating speed, resembling the way design speed is modelled. Speed prediction models, however, also show that the operating speeds in Dutch curves are well above the design speeds (Farah et al., 2017), so curve geometrics such as radius and superelevation do not have a direct (causal) relationship with operating speed. A correlation however does exist, because with smaller radii lower speeds are selected, so in some way curve geometric characteristics are perceived by the drivers and used to select an operating speed. Differences in design speeds and operating speeds well over 20 km/h (Farah et al., 2017) could thus be explained, because driver characteristics and perception are usually overlooked in setting the design speeds. An understanding of how drivers select their operating speeds could lead to a design practice in which driver characteristics and perception are taken into account, and to a design based on human behaviour instead of physics alone.

The available literature on driver behaviour in curves generally remains rather conceptual though, but it gives some insights towards speed selection in curves. For example, driving task descriptions (Campbell et al., 2012; McKnight & Adams, 1970) give insights in the different zones of curve driving: curve not yet in sight (anticipation), curve in sight (discovery), within a curve (negotiation) and exiting a curve (leaving). These zones need different tasks, such as turning the steering wheel in curve negotiation. In terms of speed estimation by the driver, speed signs and curve radius are mentioned as primary indicators. The perception of the curve radius itself becomes better when getting closer to the curve, being at best at the start of the curve itself (Riemersma, 1988). Transition curves however could distort the perception of curvature (Riemersma, 1989). In curve negotiation the tangent point is the spot that gets the most attention of the driver (Land & Lee, 1994; Lappi & Lehtonen, 2013; Shinar et al., 1977). The perception of curve cues is an automated process (Neisser, 1976) of perceptual exploration and the memory drivers have of curve cues. The memory of different curves is stored in schema and help drivers to quickly select a speed based on cues they perceive (Charlton & Starkey, 2017a, 2017b; Ranney, 1994). This speed selection is a skill-based process (Ranney, 1994) and does not involve active thinking while driving, because it is based on experience and memory. At the skill-level, errors could for example happen when drivers do not perform an attentional control over the intended action and therefore a wrong routine is activated (Reason, 1990). This means that not enough attention is paid to the curve cues, or curve cues are misinterpreted and the wrong speed is selected (Stanton & Salmon, 2009).

These conceptual insights lack quantitative variables measuring their influence on speed choice. Such variables therefore cannot be incorporated in complex designs. To our best knowledge no research has been done on the cues that drivers use to choose their operating speeds in curves. The aim of this research is to explore which curve characteristics drivers use to select an operating speed to drive through curves. Because of the explorative nature of this research, a good method to start gaining insight into these variables is to ask the drivers themselves (Proctor & Zandt, 2008). A survey is a useful method to ask a large sample of drivers for their reasons to select an operating speed through curves. Since the driving task is mainly visual (Hills, 1980; Sivak, 1996), a well-known method is to show respondents photos and pictures as stimuli (Charlton & Starkey, 2017a). We further elaborate on this in the method section.

2.2 Method

This section first presents the main research questions, followed by the survey design, curve selection, survey respondents and analysis approach.

2.2.1 Research questions

The main question in this explorative study is: Which curve cues are used by Dutch drivers to select their operating speed through a curve? To answer the main question, two sub-questions were defined as follows:

(1) Which reasons (variables) for selecting their operating speed are identified by respondents?

(2) How are these reasons related to actual curve characteristics?

2.2.2 Survey design

The survey was designed in Dutch using Google Forms. First, information about the aim of the survey was given to respondents, followed by an informed consent which the respondents were asked to sign to give permission to use their anonymous data. The main part of the survey showed pictures of pairs of curves. Static pictures were used to prevent biases that could arise based on perceived speed (or deceleration) in videos. Videos have inherent cues based on locomotion (Charlton & Starkey, 2017b). A video incorporating vehicle speeds could be chosen by the respondents based on these dynamics, instead of its curve characteristics, which are the main aim of this research. To overcome this the same speeds could be used in the videos but that would result in very unrealistic videos. In addition, comparing pairs of videos is more difficult and time consuming for participants than comparing pictures. Therefore, we chose to use pictures instead.

Each presented picture included a pair of curves. Respondents were asked to compare them and pick the curve through which they think they would drive faster. Eight different curves were compared to each other, resulting in 28 different comparisons. The comparisons were shown in random order to overcome sequence bias. The goal of these comparisons was two-fold. First by comparing all 8 different curves to one another, it would be possible to rank the curves in terms of how often they were chosen. The second and main goal was to activate the thought process needed to answer the question which followed the 28 comparisons: “What are your reasons to drive faster in a curve?”. Speed selection in curves is probably a skill-based process (Ranney, 1994) which does not involve active thinking while driving. By asking the main question after a dichotomous comparison task in which respondents were asked to choose between two curves, it was assumed that this has activated their thinking about speed selection. A dichotomous answer option was chosen over a Likert Scale because a dichotomous option forces the respondent to think about differences, without having the easy “neutral” option. This could give insights into particular schema or scripts being activated. Furthermore, by not providing pre-stated answer possibilities (as in (Kanellaidis, 1995)), it was hoped that this would lead to a variety of reasons mentioned. Finally, in the last part of the survey the participants were asked to optionally provide information regarding their gender, age and driven kilometres a week.

2.2.3 Curve selection

The curve selection was done based on three predetermined road geometric characteristics that were encountered in the literature on the perception of curve characteristics (Calvi, Bella, & D'Amico, 2018; Fildes & Triggs, 1985; Riemersma, 1988): radius, deflection angle and number of lanes. All selected curves were right turning to prevent bias towards turning direction, because drivers behave differently in curves with different turning directions (Othman, Thomson, &

Lannér, 2010). In addition, there is larger variation in the curve radius in right turning curves because they include curves with deflection angles between 50 and 300 degrees. The 8 selected curves are presented in Table 2-1 together with their geometric characteristics. 'R_h' is the horizontal radius measured in meters, this is thought to be the major cue in speed prediction (Campbell et al., 2012; Riemersma, 1988). 'R_v' is the vertical curvature in meters with a positive number being a sag curve and a negative number being a crest curve. It is measured because vertical alignment is thought to influence the perception of horizontal radius (Bella, 2015). 'i' is the superelevation in %, which plays a major role in setting design speeds. 'W' is the road width measured in meters and number of lanes is an integer number. Both are included because they might play a different role in curve perception. In order to measure the visibility of the curve in the pictures two different sight distances were measured, using the point where the picture was taken from. 'S_r' is the sight on length of road visible in meters, this is the length of road which is visible from the standpoint of the driver, which can be obstructed by a vertical crest curve, or obstacles in the inner curve, such as guardrail. 'S_t' is the sight on the length of the visible trajectory of the road. The trajectory of the road is also visible through elements parallel to the road geometry, such as guardrail, trees, fences, earthworks, etc. These elements also contribute to the prediction of the path of the road (Lehtonen et al., 2014). This makes 'S_t' a broader concept than 'S_r'. Figure 2-1 illustrates an example of measuring 'S_r' and 'S_t' in curve A15**.** The sight on the road itself is obstructed by guardrail (the dashed-dotted line), so only the black part of the road is visible which is measured as 'Sr', the grey part of the road is invisible to the driver. The treeline in the outside curve gives the driver sight of the trajectory of the curve until the end of the curve because the trees are high enough to be visible over the entire length of the curve. The length of the treeline is measured as 'St'. Since A15 does not have a vertical crest curve, this does not obstruct 'Sr' or 'St'. In some cases, 'S_r' and 'S_t' are the same, because there are no extra trajectory cues available than the road itself. Not the entire deflection angle is visible in the pictures. Therefore the visible angle '$Ø_v$' is taken into account, which is measured in gradians and represents the angle of the visible trajectory of the road (S_t) as shown in Figure 2-1**.**

Table 2-1 Geometric characteristics of the selected curves.

Curve ID	R_h (m)	R_v (m)	i (%)	W(m)	Number of lanes	S_r(m)	S_t(m)	$Ø_v$ (g)
A01	239	-57035	4.5	15.44	3	138	159	42
A02	249	∞	4.5	10.77	2	134	134	34
A09	180	-2551	7.0	11.77	2	80	275	97
A15	60	10419	3.0	8.70	1	63	192	204
A28	64	∞	7.0	8.08	1	103	103	102
A50	206	12939	4.5	8.57	1	183	183	57
A59	255	3416	7.0	7.80	1	122	263	66
A77	346	10171	5.0	7.21	1	140	226	42

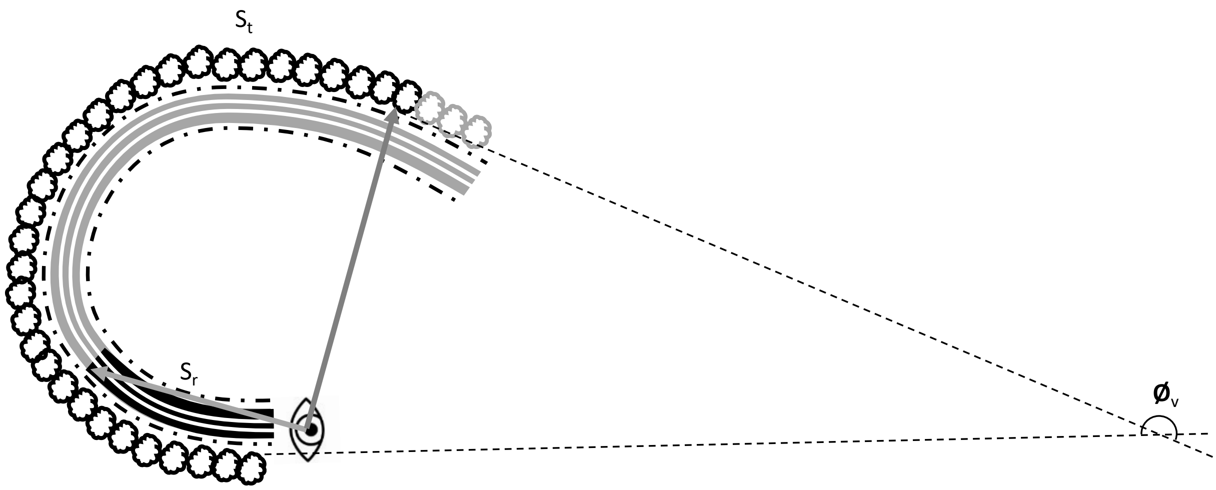


Figure 2-1 An example of measuring sight distance on road 'Sr', sight distance on trajectory 'St' and visible angle 'Øv' in curve A15, of which the picture is shown in Figure 2-2.

Curves A01, A02 and A59 were selected as a trio to compare the effect of the number of lanes present, while the radius remained similar. Curves A50 and A77 were selected as a duo in which the radius was different, but the number of lanes remained the same. Curves A15 and A28 were selected as a duo in which the visible angle changed while the radius and the number of lanes remained the same. Finally, curve A09 was selected as an extra curve to fill the gap in radii between 64 and 239 meters. Curve ID's were created based on freeway numbering in The Netherlands. The actual locations are hyperlinked in Table 2-1.

As introduced, it is the main goal of this explorative study to identify curve cues which drivers think are important when selecting their operating speed. Eight curves with unique characteristics do not provide enough data to perform meaningful statistical analyses on curve characteristics. The amount of 28 comparisons, however, were assumed to generate active thinking by the respondents to answer the main question. This is hoped to identify reasons for driving faster through a curve. At the same time, 28 comparisons are a fair amount for participants to complete in such a survey. At the start of the survey respondents were informed that it would take about 5 minutes to complete it.

The pictures were taken from CycloMedia (Van Hasselt, 2009), a database containing approximately 168 million pictures of 1 million kilometres of roads in the Netherlands. Pictures are updated frequently, so various conditions of each road are available. CycloMedia pictures show the viewing perspective in between that of a truck driver and a passenger car driver. Pictures with about the same weather conditions were selected and with as few other vehicles in the picture. Pictures were selected that were taken at the start of the curve itself, because that is where drivers can perceive the curve best (Riemersma, 1988). The pictures also show the tangent point of the curve approximately in the middle of the picture, because the tangent point is the spot that is looked at the most by the driver (Land & Lee, 1994; Lappi & Lehtonen, 2013; Shinar et al., 1977), and therefore resembles the most natural viewing direction.

Figure 2-2 Overview of curve pictures shown in the survey taken from CycloMedia Technology B.V. Curve ID's were created based on freeway numbering in The Netherlands.

2.2.4 Survey respondents

The survey was spread throughout social media, such as LinkedIn, Facebook, Twitter, and mailing lists to colleagues, friends, family, alumni groups, etcetera. This resulted in 820 responses, of which 819 gave consent to use their input. All respondents were Dutch. In total 74% of the respondents were males (n=607) and 25% (n=206) were females, 1% (n=6) did not answer the question or did not want to disclose their gender. The age of the 689 respondents (not all respondents answered the age question) ranged from 18 (which was the set minimum) to maximum 78 (mean = 41.3; Std.=11.9). Frequencies of age and gender are shown in Figure 2-3(A), while Figure 2-3(B) shows the distribution of the amount of km the respondents drive per week.

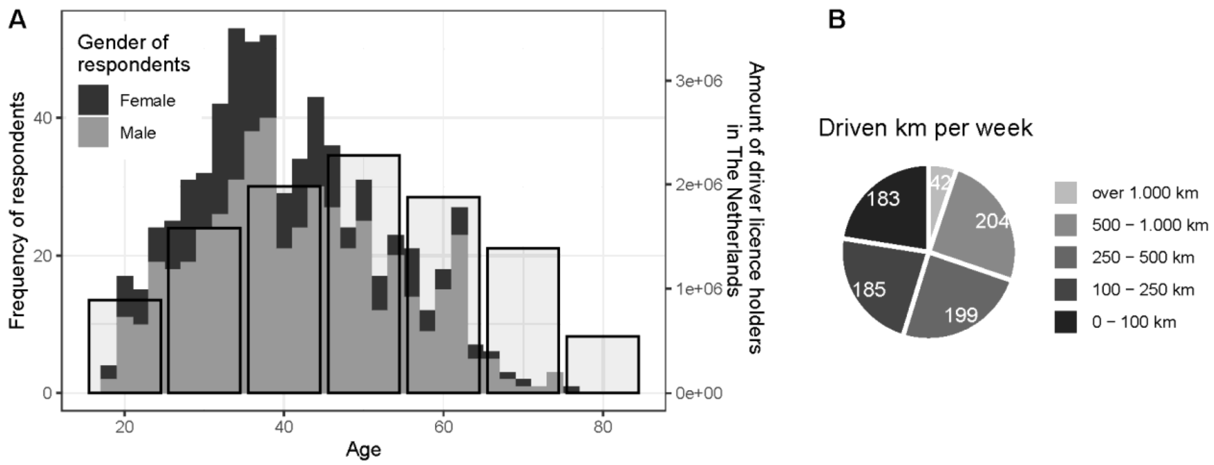


Figure 2-3 (A) – Bar chart showing the distribution of ages of the respondents per gender, in light grey boxes the distribution of driver license holders in The Netherlands is shown per age group in 2014 (Transport and mobility 2016, 2016); (B) – Pie chart showing the distribution of driven kilometers per week by the respondents.

Based on the people owning a driver's licence in the Netherlands (*Transport and mobility 2016*, 2016), our sample shows an over-representation of the 30-40 age group, and an under representation of the 60 – 80 age group (Figure 2-3 A). Our sample also shows an over-representation of male drivers while the distribution of kilometres driven per week is on average similar (*Transport and mobility 2016*, 2016). Given the exploratory nature of this research and the fact that we had a relatively large sample of respondents (819), the slight over-representation of ages 30 – 40 and under representation of ages 60 - 80 does not pose a problem. The over-representation of males in the sample is discussed further in the Results and Discussion section.

2.2.5 Analysis approach

The analysis approach consisted of three main steps. First, the reasons behind choosing to drive faster on one curve over the other, based on the open question, were investigated and then grouped in 21 different variables. The grouping was based on sets of words which had the same meaning and pointed in the same direction. For instance, the variable "visibility" is defined by words as looking, seeing, and visible. "Visibility" in that way is a variable which is measurable as a sight distance. The variable "overview" was created because the Dutch word "overzicht" was mentioned often by the respondents. It is a hard to measure variable, which has a more holistic and contextual connotation. By going through the responses, a list of synonyms was created, which was then used to categorise answers into one or more variables. A cluster analysis on respondents' answers was conducted to identify how variables would be clustered.

After the analysis of the variables mentioned by the respondents, it was counted how often each respondent chose a certain curve. In the comparison task eight curves were compared to each other. So, a curve could be picked a maximum of seven times and a minimum of zero times. The amount of times a certain curve was selected leads to a ranking, and the curve which was picked most often, was assumed to be the curve which the respondent thought to drive through with the highest speed. This ranking was compared in a qualitative manner to the actual curve characteristics in order to gain insight in which curve characteristics relate to operating speed selection.

Finally, data from specific groups of respondents within the survey were further analysed. These groups do not constitute a representative sample of the population of Dutch drivers. However, each group is represented relatively well in this sample, and we look into the results of these specific groups to gain insight into the overall usefulness of the outcome of the first two steps.

2.3 Survey results and discussion

2.3.1 Reasons for driving faster

The open question in the survey gave much insight into the reasons why respondents would drive faster through a curve. These answers were grouped into 21 different variables and summarised into 4 different commonly identifiable categories as summarized in Table 2-2. The first category relates to the road environment and its surroundings. The second category concerns the road geometric characteristics of the curve itself. The third category are driver related factors, and the last category refers to external influences. Table 2-2 shows in detail the different identified variables and the number of respondents that mentioned these variables. Each respondent provided on average more than one reason, so the sum of n in the table is larger than the number of respondents (819).

Table 2-2 Reasons for driving faster.

Categories and variables	%	N
Road environment and surroundings	*82%*	*668*
• Visibility	71%	583
• Overview	34%	275
• Presence of signage	20%	162
• Presence of trees	9%	77
• Presence of guardrail	6%	48
• Presence of obstacles	5%	43
• Guidance	5%	39
• Marking	3%	22
Geometric road characteristics	*57%*	*465*
• Number of lanes	35%	284
• Radius	28%	229
• Road width	17%	136
• Road type	5%	38
• Vertical alignment	5%	38
• Deflection angle	4%	32
• Superelevation	3%	24
Driver related factors	*21%*	*172*
• Driving style*	9%	70
• Familiarity	3%	25
• Type of vehicle	1%	9
External influences	*16%*	*130*
• Pavement conditions	7%	60
• Traffic conditions	5%	41
• Weather conditions	3%	28

** This includes reasons regarding feelings, hurry, status, excitement, fun, safety, etc.*

The following sub-sections discuss the results in Table 2-2 per category.

2.3.1.1 Road environment and surroundings

Elements of the general appearance of the curve were mentioned the most by the respondents. These include visibility and overview, but also the presence of signage, trees, guardrail, obstacles, markings and guidance in general. Having a good overview and being guided through the curve were generalised reasons having to do with most of the variables. This implies that drivers use the whole curve environment to select their operating speed. Visibility was mentioned in most of the answers. It includes words as looking, seeing, and visible. Visibility being the most mentioned variable confers the statement that 90% of the driving task is visual (Hills, 1980; Sivak, 1996). The answers focus on the need to see where the road is going, which resembles the visible angle '$Ø_v$'. A specific type of visibility is mentioned as 'overview'. In total 34% of the respondents gave a clear statement about the importance of overview in choosing their speed. This is a much broader concept than regularly used as different sight distances in geometric road design and which corresponds to trajectory planning and looking ahead (Lehtonen et al., 2014). It cannot easily be quantified through a measure in the field, because the answers given by respondents related to overview are not related to a single curve characteristic or set of characteristics.

One fifth of the respondents answered that when there are no curve signs they would drive faster. Since only 20% of the respondents mentioned curve signage, it is possible that the other 80% of the respondents did not notice the signage, perhaps due to some form of inattentional blindness (Costa et al., 2014; Martens, 2018) while performing the curve assessments. Another explanation could be that the other 80% just do not value the presence of signage.

When a respondent mentioned the presence of trees in their answers, they had different and conflicting reasons, either as giving guidance, or obstructing the visibility of the curve. A distinction between inner and outer curve was not made in the present study, but earlier simulator studies have shown that trees in the inside curve trigger drivers to reduce their operating speeds in curves (A. Calvi, 2015; Jamson et al., 2015). Respondents usually mentioned the presence of guardrail as an obstacle and restricting the ability to look ahead, but also in reference to guidance. Guidance as a general term was mentioned by 5% of the respondents. It was usually mentioned as leading towards selecting a higher speed. Marking as a guiding principle did not seem to play a big role because marking in all the pictures was adequate, and there was not much variability among the curves.

2.3.1.2 Geometric road characteristics

Over half of the respondents mentioned reasons related to the geometric characteristics of the curve. This includes the number of lanes, the radius, the type of road, vertical alignment, angle and superelevation. When looking into these variables, the answers of the respondents show strong relation with visibility and overview. This implies that a single curve characteristic needs to be evaluated within the context of the entire curve surrounding. Respondents reason that when more lanes are available, their operating speed will be higher, but some respondents mention the opposite; they do not like other traffic besides them. Having the possibility to overtake makes it more attractive to drivers to travel with higher speeds. It also corresponds to the relation between more lanes and larger radii mentioned in older Dutch design guidelines (*ROA - Knooppunten en Aansluitingen*, 1993). These guidelines were used to design many curves which are still present in today's freeway system in The Netherlands, and therefore in the memory of many drivers. This points towards drivers' expectations regarding the relation between more lanes and bigger radii. Results of simulator studies (Alessandro Calvi, 2015; Calvi et al., 2018) also show this, as well as speed observations made on Dutch freeway curves (Farah, Daamen, & Hoogendoorn, 2019). Respondents state that if the road width itself increases, so does their operating speed. A total of 35 respondents mentioned both road width and number of lanes, making it a minority in the group of respondents mentioning road width. It is therefore unclear whether road width is perceived and interpreted in the same way as number of lanes. Curve radius itself is quite a technical term, so mentions of sharpness, curviness, etcetera have been included under this variable as well. This is supported by earlier research on perception of curves (Riemersma, 1988) which identified these types of words to correspond to radius. Respondents usually mentioned that when a curve has a larger radius, they would select a higher speed. Different types of road (main carriageway, connector road, etc.) and discontinuities (exits, freeway junction, fork, etc.) were mentioned by very few respondents to influence their speed choice, perhaps because the pictures did not explicitly show this type of road sections. Road type seems to refer to the concept of self-explaining roads (Walker, Stanton, & Chowdhury, 2013) and drivers' ability to construct expectations on upcoming elements (such as sharp curves) based on the general road layout. Respondents answered they would drive faster on a main carriageway compared to connector roads. Vertical alignment refers to all mentions of hilliness, grades, going up, acclivity, etc. Respondents reasoned that crest curves obstruct overview but up-going slopes gave them a better overview of the situation. There is also evidence that drivers (in simulators) chose different speeds when confronted with crest or sag curves, based on a distortion of their perception of the horizontal curvature (Bella, 2015). Deflection angle is a variable used to capture all the mentions of angle, long curves and degrees. Deflection angles have earlier been shown to be of significant importance (Riemersma, 1988) to curve perception. Superelevation is hard to see in a picture, probably therefore only a few of the respondents mentioned it as a reason. So, here we see a difference between curve perception and curve design. Superelevation is a variable of major importance in curve design but seems to play a minor role in curve perception.

2.3.1.3 Driver related factors

Much fewer respondents gave insights into reasons that relate to their own driving style or other personal motivations. We use the term driving style as a generalisation of reasons regarding feelings, hurry, status, excitement, fun, safety, etc. Different driving styles (positive and negative) were included in this variable and recent research which focussed more on driving style showed differences between moderate and aggressive drivers (Deng et al., 2018). This type of differentiation could not be made based on the answers given in this survey, because only 9% of the respondents gave answers in this direction without mentioning it being negative or positive. Some of the respondents mentioned they would go faster through a curve when they are familiar with the curve and know what is coming. Naturalistic driving studies have also shown a relation between familiarity and higher speeds (Wu & Xu, 2018). The type of vehicle the respondents drive was mentioned by only 1% of the respondents. An Australian study (Salmon et al., 2014) showed that drivers of different types of vehicles have different schema of the same situation. A memory schema helps the driver optimize their behaviour based on expectations stored in memory. These schema help drivers select a speed based on cues they perceptually receive (Charlton & Starkey, 2017a, 2017b; Ranney, 1994).

2.3.1.4 External influences

External influences are variables that lie outside the spatial design and the driver. The reasons mentioned by the respondents related to pavement, traffic, and weather conditions. Pavement conditions include maintenance, quality or the colour of the asphalt. Newer asphalt appeared more reliable to drivers and give them confidence in driving faster. Traffic conditions related to other traffic which could limit drivers' speeds or following behaviours. Some respondents also mentioned that they do not want to slow down other traffic. And finally, respondents mentioned that bad weather conditions would lower their operating speeds.

2.3.2 Cluster analysis

The 819 respondents used different combinations of variables in their answers. The count of those variables was given in Table 2. This table summarised the variables into commonly used categories, and not how these variables were combined in answers. Hierarchical clustering of the combined variables in respondent answers was conducted using 'ClustOfVar' package in R (Chavent, Kuentz-Simonet, Liquet, & Saracco, 2012) which generated the dendrogram in Figure 4.

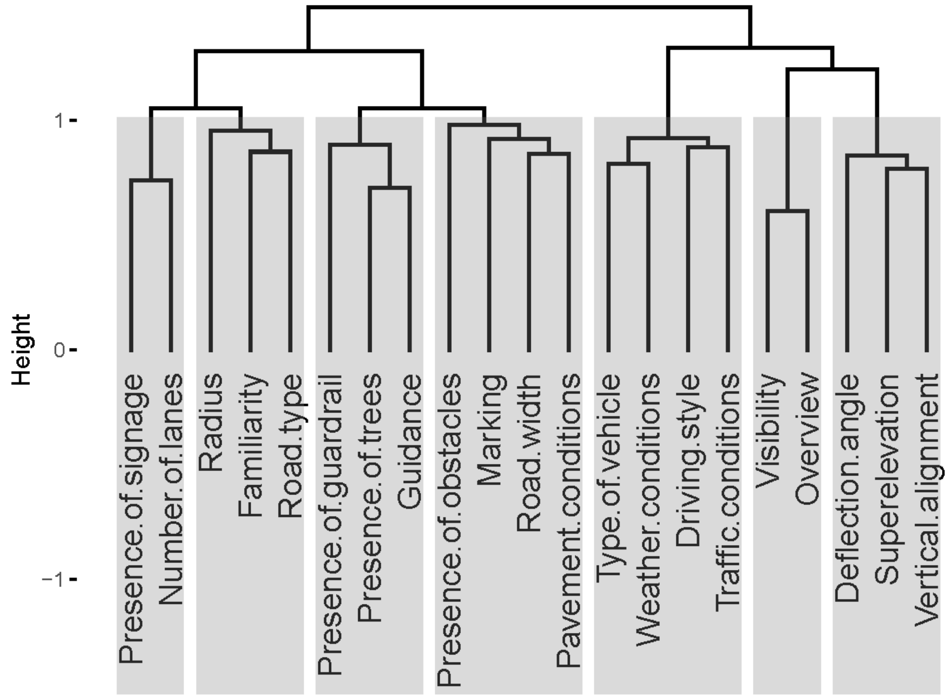


Figure 2-4 Cluster dendrogram of the variables used in the answers of the respondents.

The dendrogram in Figure 2-4 shows seven identifiable clusters of variables (height above 1.0) used in the answers of the respondents. The clustering of radius, familiarity and road type suggests that drivers know what the radius is going to be, based on previous experiences. The presence of guardrail, trees and guidance might suggest that both trees and guardrail are thought of as either guiding elements in a curve, or that these obstruct guidance. Marking, road width and pavement conditions all have relations to the carriageway itself and this cluster might indicate how the road looks to drivers. The type of vehicle, driving style, and external weather and traffic conditions are closely related to each other in respondents' answers, and indicates that how drivers respond to external circumstances varies with both driver and vehicle characteristics. Visibility and overview are clustered, which appears logical because the term overview ("overzicht" in Dutch) is treated as a linguistically derived variable of visibility ("zicht" in Dutch) in this analysis. The clustering of deflection angle, superelevation and vertical alignment could hint at how well a curve is recognisable, since it is closely related to the visibility cluster. The cluster which groups the number of lanes with presence of signage is less obvious to explain, but could be interpreted as how clear the sharpness of the curve is 'readable' from cues other than guidance or the radius itself.

2.3.3 Curve ranking

Based on the number of times respondents picked a curve throughout all the comparisons a ranking of the curves was made. Table 2-3 shows the overall ranking based on the average number of times respondents picked a curve to be the one they would drive through fastest. Table 2-3 also shows curve characteristics in order to compare these to the curve ranking.

Table 2-3 Curve ranking and curve characteristics.

Rank (most often picked to drive fastest)	Avg. pick	Std.	Curve ID	Rh (m)	i (%)	Number of lanes	S_r (m)	S_t (m)	$Ø_v$ (g)	Sign -age
1	6.06	1.23	A02	249	4.5	2	134	134	34	No
2	5.40	1.48	A01	239	4.5	3	138	159	42	No
3	3.99	1.44	A59	255	7	1	122	263	66	No
4	3.78	1.65	A09	180	7	2	80	275	97	Yes
5	3.56	1.62	A77	346	5	1	140	226	42	No
6	2.65	1.34	A50	206	4.5	1	183	183	57	Yes
7	1.26	1.16	A28	64	7	1	103	103	102	Yes
8	1.26	1.50	A15	60	3	1	63	192	204	Yes

The ranking in Table 2-3 is based on respondents' overall comparisons on which curves they think they would have driven faster, based on the pictures of the curves. Whether this would also represent actual operating speeds is still to be investigated. Speed prediction models suggest that higher operating speeds are to be expected in curves with larger radius (Hassan, Sarhan, Porter, et al., 2011; Odhams & Cole, 2004; Shallam & Ahmed, 2016). However, the curve with the largest radius (A77) in Table 2-3 was not picked the most by the respondents. If we look at the curve surroundings in Figure 2-2, we see that this probably has to do with the close surroundings of trees and therefore lack of perceived overview. The number of lanes could also contribute to this, since A77 only has one lane, which does not lead the respondents to expect higher operating speeds. The curve which was picked most (A02) has two lanes and a wide overview, since no trees are present. Both cues are mentioned to be of influence for choosing higher speeds. A further look at Table 2-3 shows that curves with more than one lane are in the top 4 curve picks, while curves with larger radii but only one lane were picked less often by the respondents.

When looking at sight distances themselves ('S_r' and 'S_t'), they do not show a similar order as compared to the average pick. When sight distances are combined with the angle, some relation exist in the picking order and *visible* angle ('$Ø_v$'). Based on the results of this survey, the more curve angle is visible (i.e. '$Ø_v$' is larger), the less often a curve gets picked as being a fast curve. This makes sense, because the further we can see does not tell anything about what we see. So, combining curve surroundings as a measure of how far we can see the trajectory of the curve with a geometric curve element (such as the deflection angle) gives a more holistic approach. Visible angle ('$Ø_v$') however still does not explain fully how speed is selected and may not be generalizable to other curves based on this research alone. This needs to be explored with a bigger sample size and statistically tested. A more probable explanation for the relation between curve characteristics and ranking is that more curves without curve signs are picked as fast curves. This is logical because curve signs are placed at small radii.

The results show that the average pick is not ranked in relation to the available superelevation (%), which is in line with the small amount of times this variable was mentioned by the respondents.

Since only eight curves were compared, we decided not to quantify correlations or do some form of dimension reduction or regression analysis.

What Table 2-3 tells mainly is that ranking of curves based on pictures is more elaborate than looking at geometric curve design characteristics alone. Other characteristics mentioned by the respondents provide more insight in the way an entire curve is perceived. These characteristics often refer to holistic variables such as overview and guidance. Quantification of such a holistic approach, or even an approach based on Gestalt principles (Čičković, 2016) is however very difficult to attain, because there are so many variables to be taken into account.

2.3.4 Specific groups within the survey

Within the respondents three groups were looked further into: experts, younger and female respondents.

The survey was spread through the personal network of the first author (road design expert and researcher), which could have led to bias in the outcomes. To check this, we searched for the use of professional and technical terms that are usually not used by lay persons in the reasons given by respondents to drive faster through curves. This led to 14% to 27% of the respondents being identified as experts, depending on which terms were used as a filter. The results showed that experts only picked curve A77 significantly more often than lay persons (χ^2 (7, n=819) = 17.73, p=0.013), the other curves showed no significant difference. This suggests that curve A77 was selected more often by the participants in the present study as compared to the entire population.

Driving experience is important in how well one can estimate how fast the driver can travel through a curve (Charlton & Starkey, 2017a, 2017b; Neisser, 1976; Ranney, 1994). This would suggest that younger respondents (age 18-23, n=36) would differ in their survey answers from older respondents (age 24-78, n=783). However, no variable was mentioned significantly more or less often by the younger respondents compared to the older ones.

Since female respondents (n=206) are under-represented in the sample, we investigated whether they assessed the curves in this study differently than male respondents (n=607). The female respondents mentioned radius significantly more often (χ^2 (1, n=813) = 4.46 , p=0.035); they never mentioned superelevation; they mentioned vertical alignment significantly less often (χ^2 (1, n=813) = 6.08, p=0.014) and also mentioned guidance and overview less (χ^2 (1, n=813) = 8.14, p=0.004, χ^2 (1, n=813) = 4.99, p=0.025, respectively). This might indicate these characteristics play a less important role for the entire population than the findings of the present study suggest.

2.4 Conclusion

The results of the survey provide some insights in driver expectations about freeway curves which can readily be applied in curve design. Insights which may be used in design are for example, the reasons mentioned by the respondents to select an operating speed in a curve indicate that overview is needed to pick up references to the trajectory of the curve, such as tree lines, guardrail or anything parallel to the curve itself. The visibility of the trajectory could be a combination of the often mentioned variables visibility, overview and radius. Visible angle could therefore be a pragmatic dimension reduction which combines both behavioural and geometric aspects in terms of perception and deflection angle. Visible angle might have influenced the picking of curves for which higher operating speeds could be selected. In a follow-up study, this could be studied with a larger curve sample and observations of actual operating speeds.

Respondents indicated that their operating speed could be higher when more lanes are present. This corresponds to the design principles in The Netherlands (*ROA - Knooppunten en Aansluitingen*, 1993) which link an increasing number of lanes to increasing radii. This means most multi-lane curves in The Netherlands have relatively large radii, so experience in driving through such curves could form expectations that in multi-lane curves higher speeds are possible. If this is indeed a generalised expectation of drivers, road designers should be careful designing small radii curves with multiple lanes because faulty routine activation by drivers could lead to errors (Stanton & Salmon, 2009) and accidents. Superelevation is of importance to design speed, and design guidelines mention that superelevation helps to detect an upcoming curve better. Based on this study however, superelevation does not seem to play a role in curve perception.

This study provides some first insights into possible directions for further research. Based on the results of this study, it is recommended that future research into predicting operation speeds in curves also incorporates variables that are identified as relevant for drivers for selecting their operating speed. Most of these variables are easy to measure, such as radius and number of lanes, others are easy to spot, such as the presence of trees and signs. Curve surroundings are not usually a variable in speed prediction models (Hassan, Sarhan, Porter, et al., 2011), but based on this study, there is good reason to include these. It is however difficult to quantify the most mentioned variable "visibility" since sight distances alone do not seem to have a clear relationship with speed. But visible angle '$Ø_v$' might prove a valuable measure which combines sight distances with radius and deflection angle. Also, the term overview was mentioned by a third of the respondents. This seems to be a holistic concept, which is hard to quantify and use in a speed prediction model. Future research should include more curve characteristics and surrounding elements in an attempt to operationalise the variable "overview" in a speed prediction model.

This research is explorative in its nature and the survey itself is basic in its design, showing only pictures of eight different right turning curves. It is difficult to gain insights in drivers speed choice based on static pictures alone (Charlton & Starkey, 2017b). The ranking differed in that of the measured speed, so further research should focus on cues based on locomotion as well, but also use a larger sample of curves and explore other research methodologies beside static pictures. Since the setting of the survey and the respondents were Dutch, results might not generalisable to drivers in other countries who may have other expectancies about curves and speed selection.

3 Analysis of Individual Speed Profiles

This chapter has previously been published as: ***Vos, J.***, *Farah, H., & Hagenzieker, M. (2021). Speed behaviour upon approaching freeway curves. Accident Analysis & Prevention, 159, 106276.*

Abstract

The actual speed behaviour when drivers approach a curve is very relevant to assess the road design and safety but is mostly overlooked in the scientific literature. Most research into curve driving behaviour is focussed at the behaviour inside the curve, although the speed selection is done before curve entry. The main objective of this research is to identify which freeway characteristics play a role in driving speed selection. High Frequency Floating Car Data, detailed reconstruction of the curves and their surroundings, as well as three dimensional sight distance analysis, were used to analyse individual speed profiles on 153 Dutch freeway curves. By defining the positions where the acceleration approaches 0 m/s^2 before and after a curve starts, the positions when the driver started and stopped decelerating upon curve entry were defined. Further correlation and regression analysis of those positions revealed that the radius of the curve is indeed a main explaining variable, as well as the speed driven before deceleration starts. Sight distances and cross section characteristics play a further role in determining the position where deceleration starts. Deceleration ends at approximately 135 meters after curve start, and the speed in a curve is also correlated with the deflection angle and length of a curve. Sight distances do not play a role in selecting the speed in a curve based on this research. Overall, the findings indicate a non-constant nature and variability of speed behaviour upon curve entry. This can be used for safer freeway curve design and to assess traffic safety based on actual speed behaviour.

3.1 Introduction

The speed which drivers select to drive in a freeway curve is of major influence on traffic safety. A speed which is too high, results in a loss of control of the vehicle due to a loss of friction (Donnell et al., 2016; Himes, Porter, Hamilton, & Donnell, 2019; Li & He, 2016). Because of this, the design of freeway curves has mostly been related to side friction factors (Fitzpatrick & Kahl, 1992). Human factors are however mostly overlooked in curve design, although it is the driver who selects the speed (Charlton & Starkey, 2017b). Understanding how drivers select their driving speeds is therefore of importance to safe freeway curve design.

Research in curve driving has mainly focussed on driving aspects when the driver is already inside the curve. Such research focusses on where drivers look (Gruppelaar, Paassen, Mulder, & Abbink, 2018; Land & Lee, 1994; Lehtonen et al., 2014; Salvucci & Gray, 2004; Shinar et al., 1977), the lateral position inside the lane (Coutton-Jean, Mestre, Goulon, & Bootsma, 2009; de Waard, Steyvers, & Brookhuis, 2004; Van Winsum & Godthelp, 1996) or the speed drivers select in a curve (Farah et al., 2019; Hassan, Sarhan, Porter, et al., 2011; Luque & Castro, 2016; Odhams & Cole, 2004). Only a few research studies have focused on the curve detection phase (Lehtonen et al., 2012), even though task descriptions state that the period just before entering the curve is most important in the perceptual, cognitive and psychomotor tasks drivers need to select their driving speeds in a curve (Campbell et al., 2012; McKnight & Adams, 1970; Shinar, 2017c). Explorative research showed that drivers take the entire curve surroundings into account while selecting their speed when entering a curve (Vos, Farah, & Hagenzieker, 2021a). It remains unclear however, which cues are of importance to the driver.

The key feature of a curve is its radius. A relatively small radius urges drivers to slow down, in order not to skid (Donnell et al., 2016; Gibson & Crooks, 1938). This means that the radius is a key element upon which drivers select their speed. Because the driving task is mostly visual (Hills, 1980; Sivak, 1996), drivers need to perceive the radius. However, from a driver standpoint the perception of a curve gets distorted in a hyperbola, which results into less well perceived curvature when the radius decreases (Brummelaar, 1975). Because it is difficult for drivers to perceive the curve radius, other factors are assumed to play a role in curve perception and speed selection such as the deflection angle of a curve (Fildes & Triggs, 1985; Riemersma, 1988; Wang & Easa, 2009). Studies on distortion in the perception of curvature were mostly based on perspective drawings as laboratory stimuli and lack therefore other static and dynamic curve characteristics (e.g., guardrail, signing or traffic). Some of these elements have however been validated in experiments or field studies, these include the transition curve (Perco, 2006; Riemersma, 1989) and vertical sag curves (Bella, 2015; Campbell et al., 2012; Wang & Easa, 2009). Visual research using eye trackers shows more visual attention towards the right, in right turning curves than to the left in left turning curves (Lappi & Lehtonen, 2013; Shinar et al., 1977), suggesting right turning curves need more attention. In both laboratory studies (Singh & Fulvio, 2007) and simulator studies (Coutton-Jean et al., 2009), it was shown that drivers use and need continuous information to assess the curvature. This includes road markings (Charlton & Starkey, 2013; Coutton-Jean et al., 2009; de Waard et al., 2004), curve signs (Charlton, 2004), road lighting and tree lines (Blumentrath & Tveit, 2014). These elements need to be visible enough though, otherwise drivers decelerate later and more sharply before curve entry (Jamson et al., 2015). Partly occluded shapes however, can still be interpreted based on knowledge about these objects (Hazenberg & van Lier, 2016). Indeed, when drivers are familiar with the road, they choose higher speeds (Wu & Xu, 2018). Drivers also choose their speed based on perceived road categories (Charlton & Starkey, 2017a) and the number of lanes present (Calvi et al., 2018), so the composition of the cross section is also relevant to the driver. Furthermore, design consistency studies showed that the tangent characteristics upstream of the curve, such as tangent length and width, influence the speed reduction (Hassan, Sarhan, Porter, et al., 2011).

Speed profiles give more insights into speed development upstream of a curve and in the curve itself and can be considered as key input for assessing the way drivers drive through curves (Dias, Oguchi, & Wimalasena, 2018). Research into speed profiles showed that the speed is not constant in a curve (Bella, 2014; Montella, Galante, Mauriello, & Aria, 2015; Wang, Guo, & Tarko, 2020), and that deceleration starts before the curve and ends inside the curve. Since drivers start to search for the upcoming curve and start to decelerate before the curve (Campbell et al., 2012; Hallmark et al., 2015; Land & Lee, 1994; Lehtonen et al., 2012; Shinar et al., 1977), the speed profile before a curve is of interest in investigating which of the elements discussed above may be of importance to the driver in speed selection. There is still a knowledge gap on this point. Since the deceleration stops within the curve, the speed selection inside the curve is also of interest to analyse the speed behaviour upon curve approach.

Therefore, the aim of this research is to gain insights into which elements are of influence on the speed profile when approaching a curve, and the speed selection in a curve. In order to gain these insights the following research questions were defined:

- Where do drivers begin to decelerate in reference to the curve start? And which elements influence this position?
- Which speed do drivers adopt in a curve? And which elements influence this speed?

The following section will discuss the research methods used to answer these questions. Section 3 analyses the data in three steps: first insights into speed profiles, correlations of speeds and curve characteristics, and regression analysis. Sections 4 and 5 discuss the results and summarize the conclusions, respectively.

3.2 Research method

In order to investigate the relationship between speed profiles and curve characteristics, we chose real world situations over laboratory settings such as simulators, to avoid any bias due to lack of motion cues or limitations in the dynamic visualisation of the road scenario (Bella, 2009; Molino, Opiela, Katz, & Moyer, 2005). We therefore selected a representative sample of freeway curves and obtained relevant and measurable curve characteristics.

3.2.1 Curve selection

We chose our curves based on a number of characteristics that are known from literature to have an influence on speed selection. Therefore, a representative selection of deflection angles, curve radii and number of lanes were considered in the freeway curves selection. Speed on off-ramps is much influenced by slowing down for the junction at the end of it, so off-ramps are excluded in the selection. Only main carriageways and connector roads in junctions were included.

This resulted in a selection of 99 road sections which include 153 curves, as presented in Figure 3-1 with their main characteristics. The curves were selected throughout The Netherlands as presented in Figure 3-2.

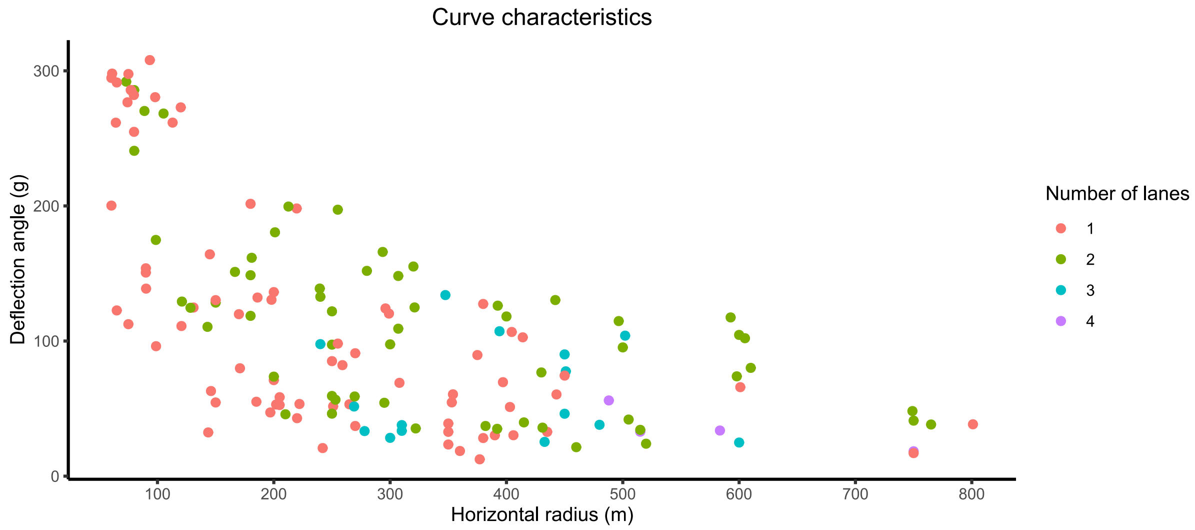


Figure 3-1 Scatterplot of main characteristics of the selected curves in this study.

Figure 3-2 Map showing the location of the curves in The Netherlands (in black).

3.2.2 Obtaining relevant curve characteristics

All of the selected curves were reverse engineered in order to have insights into the relevant geometric elements: horizontal alignment (radius, transition curves, deflection angles and tangents), vertical alignment (grades, sag and crest curves) and cross section elements (width of carriageway, number of lanes, presence of hard shoulder, superelevation, distance from side marking to guardrail).

Using the reverse engineered road alignments, sight distances were obtained every 10 meters using the Dutch "Zicht" application (Broeren, 2002) which was developed for Rijkswaterstaat (Dutch Directorate-General for Public Works and Water Management) and used for more than 20 years. In three dimensional models of the curve environment, guiding elements (which run parallel to the alignment of the curve), were identified per curve. This included the roadway itself, brake-lights (stopping sight distance), guardrail, treelines, noise barriers and curve signs as guiding elements. The position of these guiding elements was fed into "Zicht". The program stops every 10 meters along the alignment, to position a red box at the predefined offset every 5 meters in front of the driver and checks whether or not it is visible from the driver standpoint. Figure 3-3 shows a graphical example of this analysis which resulted in a definition of maximum sight distances for each guiding element, at every 10 meters along the alignment. Results from "Zicht" have been validated using dashcam video's, as shown in Figure 3-3.

Figure 3-3 On the left the analysis of "Zicht" on the visibility of the curve signs. The red object in the 3D model is the object "Zicht" checks along the alignment, in this case a curve sign, positioned above the guardrail (the dark grey line). On the right, this exact viewpoint is shown in the real life situation.

3.2.3 Speed data collection and preparation

Continuous speed profiles provide detailed information about speed development during the curve anticipation phase (Dias et al., 2018), and overcome traditional errors derived from classic point speed measurements (Hassan, Sarhan, Porter, et al., 2011; Wang et al., 2020). To create these speed profiles along the generated alignments, High Frequency Floating Car Data from Flitsmeister-users was used. This smart-phone navigation app is used by 1.6 million users in The Netherlands, of which most are personal car or van drivers. Regular Floating Car Data cannot be used to create speed profiles, but only to show speed distributions per section of road (Colombaroni, Fusco, & Isaenko, 2020). For this study, the data gathering algorithms for the app were set to a frequency of 1 Hz along the selected road sections. Data collection was executed in March, April and September 2020. These are unique speed-profiles per trip, from which acceleration-profiles can be derived. The amount of precipitation was also added for each speed profile, using the Dutch climatological radar rainfall dataset (Saltikoff et al., 2019) in order to study relations between speed and wet road conditions.

The use of speed profiles containing speed and deceleration per second allows us to find positions in the speed profile where the slope of speed versus time changes, which are called breakpoints. This method was introduced by Alfonso Montella et al. (2015), who also showed that deceleration starts in front of the curve, and ends inside the curve. Breakpoints are the main points of interest in this research, and are explained further in Figure 3-4. The positions of breakpoint 1 (BP1) and breakpoint 2 (BP2) are defined based on the acceleration profile. The position where the continuous radius starts is the reference point for the breakpoints positions (zero). The point upstream of a curve start, where the acceleration approaches 0 m/s^2, is defined as BP1 and has a negative position. The point downstream of the curve start, where the acceleration approaches 0 m/s^2, is defined as BP2 and has a positive position. The acceleration profile was smoothed using the LOESS algorithm in R (Cleveland, Grosse, & Shyu, 1992) to obtain a more realistic acceleration profile. Because of this smoothing, hardly any point will have an exact acceleration of 0 m/s^2. Therefore thresholds needed to be set to find the point closest to 0 m/s^2. Using a threshold of 1 second in which the acceleration profile is between -0.1 m/s^2 and 0.1 m/s^2 shows an optimal result for defining the positions of the breakpoints[1].

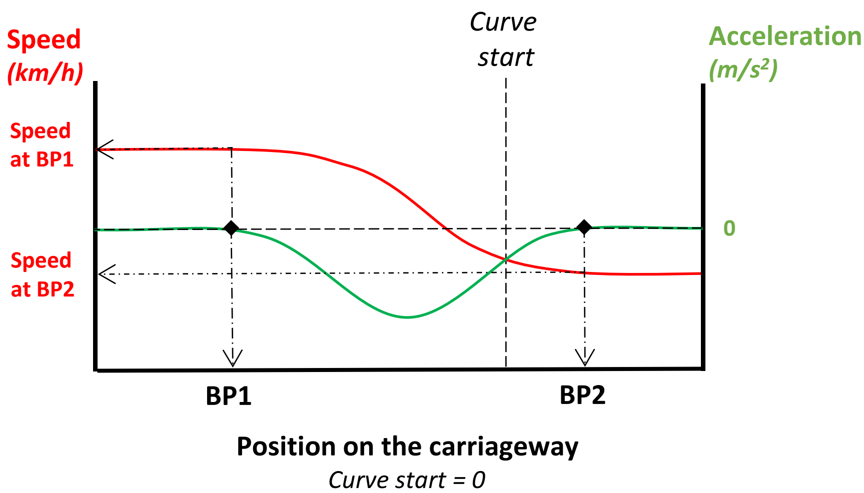


Figure 3-4 Theoretical speed and acceleration profiles drawn around the curve start.

3.2.4 Speed data filtering

All road sections were checked for road-works during the measuring period. Road works could entail extra signing, lowering speeds or distracting elements along the road. In order not to bias the outcomes in that direction, trips during roadworks were eliminated from the database.

Since we are interested in the speed selection based on curve characteristics, car following behaviour should be eliminated from the database. Every road segment in The Netherlands has a loop-detector which measures all traffic and generates average speeds and traffic volumes per minute. Hashim (2011) showed that above a headway of 5 seconds, most vehicles travelled at their desired speed. This is called a free-flow situation. Given that traffic flow is Poisson distributed, the headway is exponentially distributed. Taking an average headway of 5 seconds, the chance is around 5% that a vehicle has a headway greater than 15 seconds ($e^{-(15/5)} = 0.0497$). This is 4 vehicles per minute. In order to select trips which have a probability of 95% to have been in free-flow, trips in periods with 5 or more vehicles per minute per lane were filtered out of the database.

This results in 996,375 unique trips available in this research, on average 10,064 trips per road section (sd = 8,616, max = 41,041, min = 425). This large variability is explained because some road sections are situated in busy urban areas, and other curves are situated in remote rural areas, see

[1] These thresholds are based on a sensitivity analysis, which is shown in Appendix A.

also Figure 3-2. Some road sections also had many trips filtered out because of roadworks being present during the measurements.

Based on the loop detector data, we were able to compare our sample in the High Frequency Floating Car Data to the entire population. On average, our sample contains 9.1% (sd 7.1%) of all the drivers in the selected periods without roadworks and in free-flow. By comparing the average speeds of all the drivers, based on the loop detector data, to the sample data, it was found that the drivers in our sample drove on average 5.4 km/h faster (sd 4.9 km/h) at the loop-detector than all the drivers in the same free-flow periods. Based on the measurements of Farah et al. (2019) the sample in this research represents on average around the 60^{th} percentile of all the drivers.

3.3 Data analysis

The following sub-sections describe the analyses of the data in three steps: first we show some insights into speed profiles (3.3.1), then correlations of speeds and curve characteristics were investigated (3.3.2), and finally the results of the regression analysis for predicting the positions and speeds of BP1 and BP2 are presented (3.3.3).

3.3.1 First insights into speed profiles

In order to get a first feel of the collected data, speed profiles of curves with radii around 250 meters were compared. For these curves the median speed profile was calculated, by calculating the median speed for every meter considering all individual speed profiles. All these curves have relative tangent approaches. So, based on common speed prediction models, it is expected that all these curves have almost equal profiles (Hassan, Sarhan, Porter, et al., 2011). Figure 3-5 however shows some different characteristics in the speed profiles and breakpoints. This leads us to the hypothesis that other curve characteristics than curve radius alone might explain these differences. And indeed, when looking at the dashcam pictures in Figure 3-6, we see different road layouts in terms of different cross sections and surroundings.

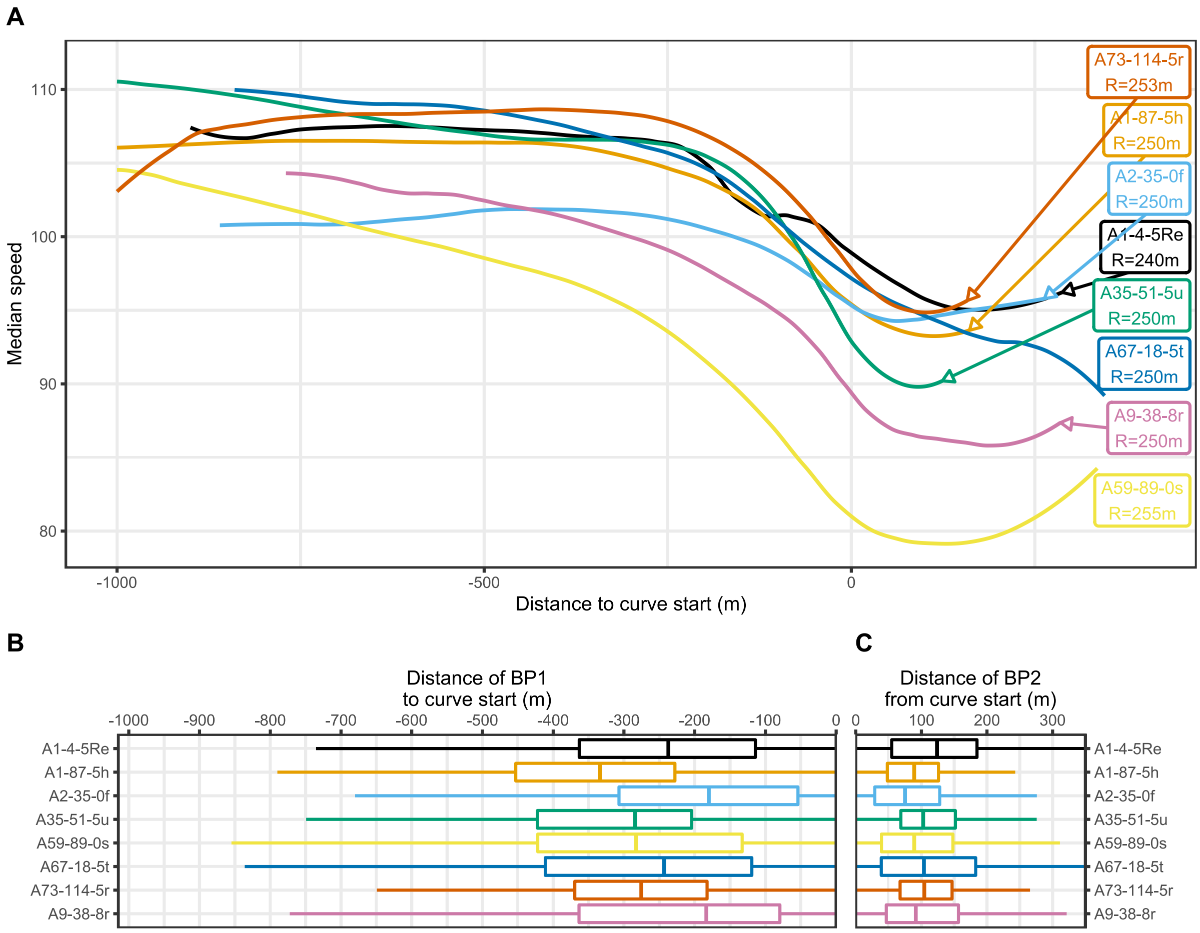


Figure 3-5 Speed profiles of eight curves with radii around 250 m and information about their breakpoints. A) shows the profiles of median speeds of all measured speeds per curve, relative to the start of the curve radius. A note to profile "A1-4-5Re", which shows a bump between 250 and 50 meter before the curve start. This bump is probably due to an overpass of around 110 meter at this location, which caused GPS inconsistencies. B) shows boxplots of the position of BP1 per curve. C) shows boxplots of the position of BP2 per curve.

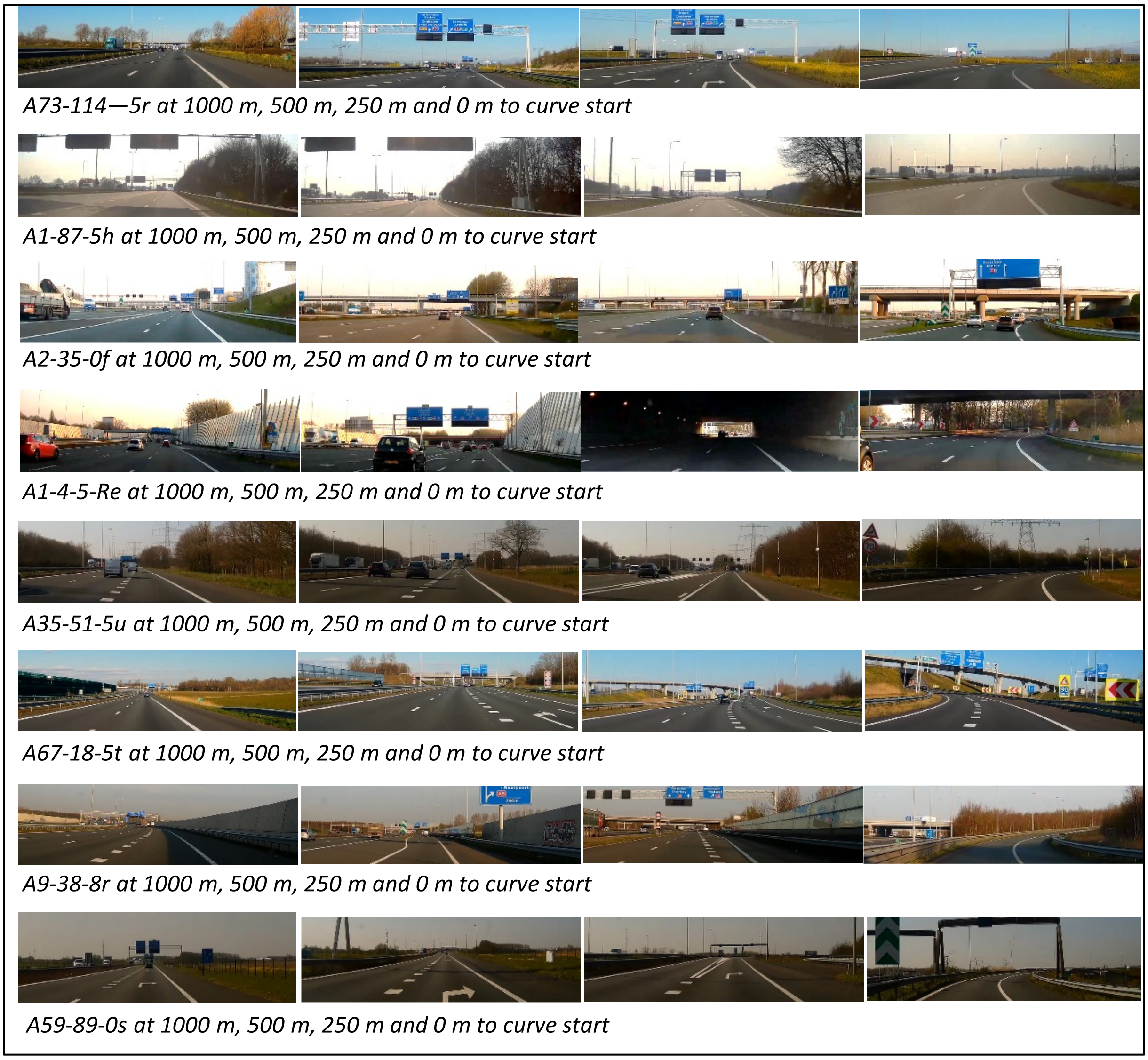


Figure 3-6 Dashcam pictures of the actual carriageways taken at 1000m (most left picture), 500m, 250m and 0 m (most right picture) to the curve start of each speed profile shown in Figure 3-5.

3.3.2 Correlations of speed, deceleration and positions of breakpoints 1 and 2 to curve characteristics

The positions of BP1, BP2 together with the speeds at BP1 and BP2 are identified as variables which determine the speed profiles. The average deceleration is derived from those two points. Correlation analysis between these five variables with curve geometry and sight distances are presented in Figure 3-7. In Figure 3-7 only variables which have at least one correlation coefficient above 0.25 or below -0.25 are shown. All shown correlation coefficients have a significance of $p<0.001$. The variables ’Curvature Change Rate’, ’Deflection angle’ and ’Length of curve’ include both the transition curves and circular curve. The ’number of usable lanes’ are the available lanes to the driver, either all available lanes on a carriageway, or the available lanes to pre-sort in the direction of the curve. The ’Ratio A to R’ represents the value of A-value of the clothoid divided by the horizontal radius in meters, and is therefore related to the length and angle of the transition. The ’visible angle’ is defined as the amount of angle which is visible based on any parallel guiding element, as explained in Vos et al. (2021a) and the ’visible length’ is the amount of length of the curve which is visible. All individual speed profiles have been used in the correlation analysis in order to account for individual differences in speed profiles and their respective positions of the breakpoints. Even though Figure 3-7 does not show correlation coefficients above 0.5 or below -0.5, some general conclusions can be drawn, even though speed prediction models usually only report correlation coefficients above 0.4 when using multiple variables (Hassan, Sarhan, Porter, et al., 2011; Llopis-Castelló, González-Hernández, Pérez-Zuriaga, & García, 2018). Since we have used all individual speed profiles in our analyses and analyse single variables, we expect relative low correlations. In behavioural sciences a correlation coefficient between 0.3 and 0.5 is defined as "medium", below 0.3 as "low", and above 0.5 as "strong" (Cohen, 1988). Distance of BP1 to the curve start, average deceleration and the speed at BP2 show the largest correlations with curve geometrics and sight distances.

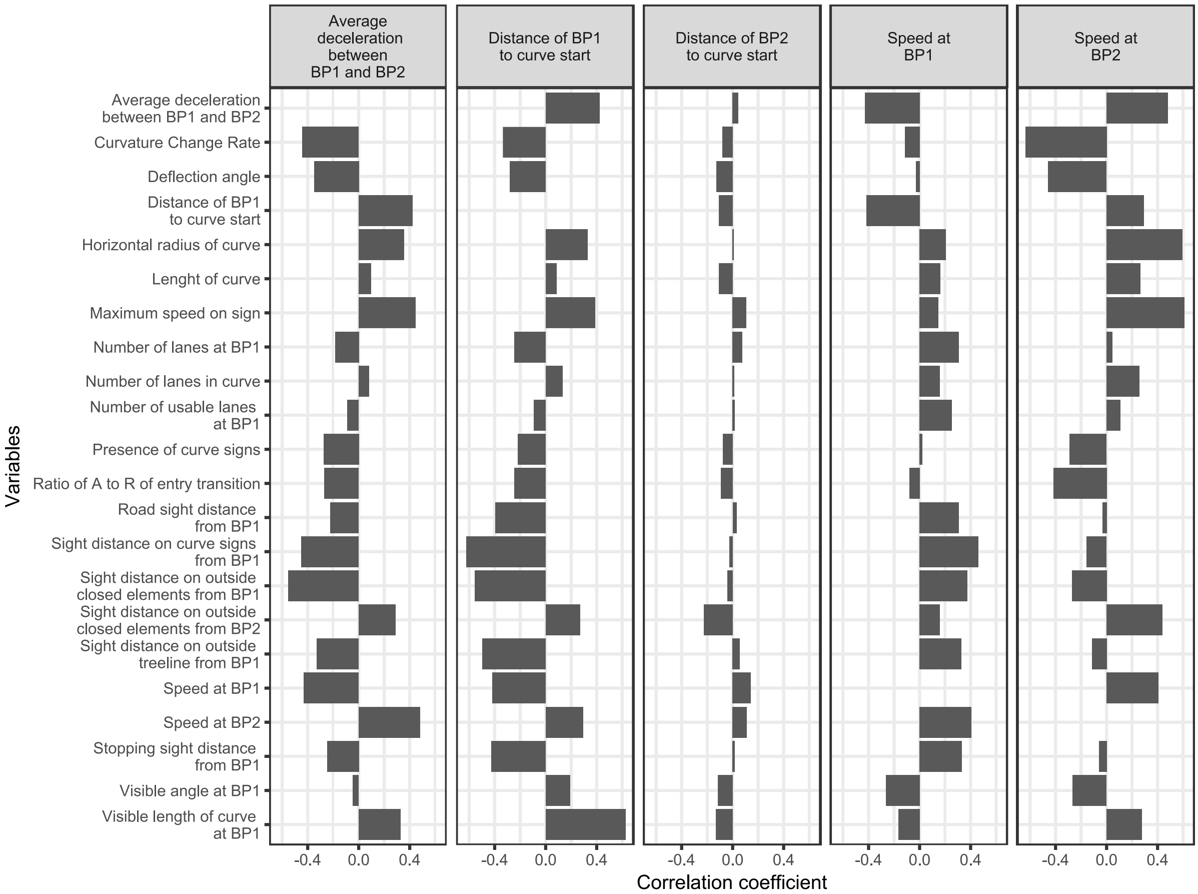


Figure 3-7 Correlations between variables which determine speed profiles and variables which determine the curve.

The speed at BP2 seems to be correlated with the speed at BP1, suggesting a relation between speed outside and inside a curve. Speed at BP1 is also correlated with the position of BP1, which is to be expected: faster driving needs more deceleration length. Sight distances on guiding elements are also correlated with the position and speed at BP1: when present, guiding elements such as closed elements (e.g., noise barriers) or curve signs have a higher correlation with the position and speed at BP1 than stopping sight distance or road sight distance. The variable that is most correlated with the distance of BP1 is however the visible length of the curve.

Speed at BP2 is correlated more to the curve geometric elements such as Curvature Change Rate (CCR), deflection angle, horizontal radius, transition curve and number of lanes. A relative large correlation can also be observed between the speed at BP2 and the maximum speed sign and presence of curve signs. Also the sight distance available on guiding elements is correlated with the speed in a curve. The position of BP2 is hardly correlated with anything, suggesting that geometric elements and sight distances do not influence the position of BP2. The average deceleration is correlated with the same geometric elements as the speed at BP2. Average deceleration however seems to be more correlated with sight distance on the guiding elements than the speed at BP2 does.

In the above paragraphs we have discussed the correlations in Figure 3-7. These all met the threshold of a correlation coefficient above 0.25 or below -0.25. It is also of interest to see which variables did not meet this threshold. The introduction mentioned that the curve direction influences driver behaviour, but this was not found in this analysis shown Figure 3-7. Also sag curves in combination with the horizontal curve were mentioned to influence driver perception, but this did not show in Figure 3-7. Superelevation is of major importance in using design speeds to design a curve, however it did not correlate to any of the breakpoints. Road categories were also identified in the introduction to influence the driver. Since only freeways were examined, we focussed instead on types of discontinuity. Discontinuities are transitions between two road-sections which limits the amount of lanes available for a driver in a certain direction because of pre-sorting. However, the different types of discontinuities did not correlate to any of the breakpoint variables. The number of usable lanes in the direction of the curve at a discontinuity takes pre-sorting into account, and even usable lanes are less correlated with BP1 than all lanes in the cross section at BP1. So, no direct correlation of discontinuity or pre-sorting with BP1 and BP2 variables was found. Most of the sight distances to guiding elements were satisfactorily correlated with the breakpoints. The positions from which sight on the curves start, or where the first 100 m of the curve is available to the driver, however did not correlate at all with BP1 or BP2 variables. And only the presence of curve signs as guiding elements seemed to correlate to the breakpoints; guardrail, treelines or closed elements did not. Finally, external weather effects such as daylight and precipitation also were not found to correlate to the breakpoint variables.

3.3.3 Regression analysis

Regression analysis was used to explore the relationship between the positions and speeds of BP1 and BP2 and the explanatory variables. The horizontal radius of the curve is the defining variable of a curve. Figure 3-8 clearly shows relations of the horizontal curve radius to the distance of BP1 and the speed at BP2. The position of BP2 is loosely correlated with the radius of the curve. The speed at BP1 is not correlated with the horizontal curve radius because it is assumed that drivers chose an optimal desired speed and are not being influenced by the horizontal radius, and indeed in Figure 3-8C a very scattered plot is shown.

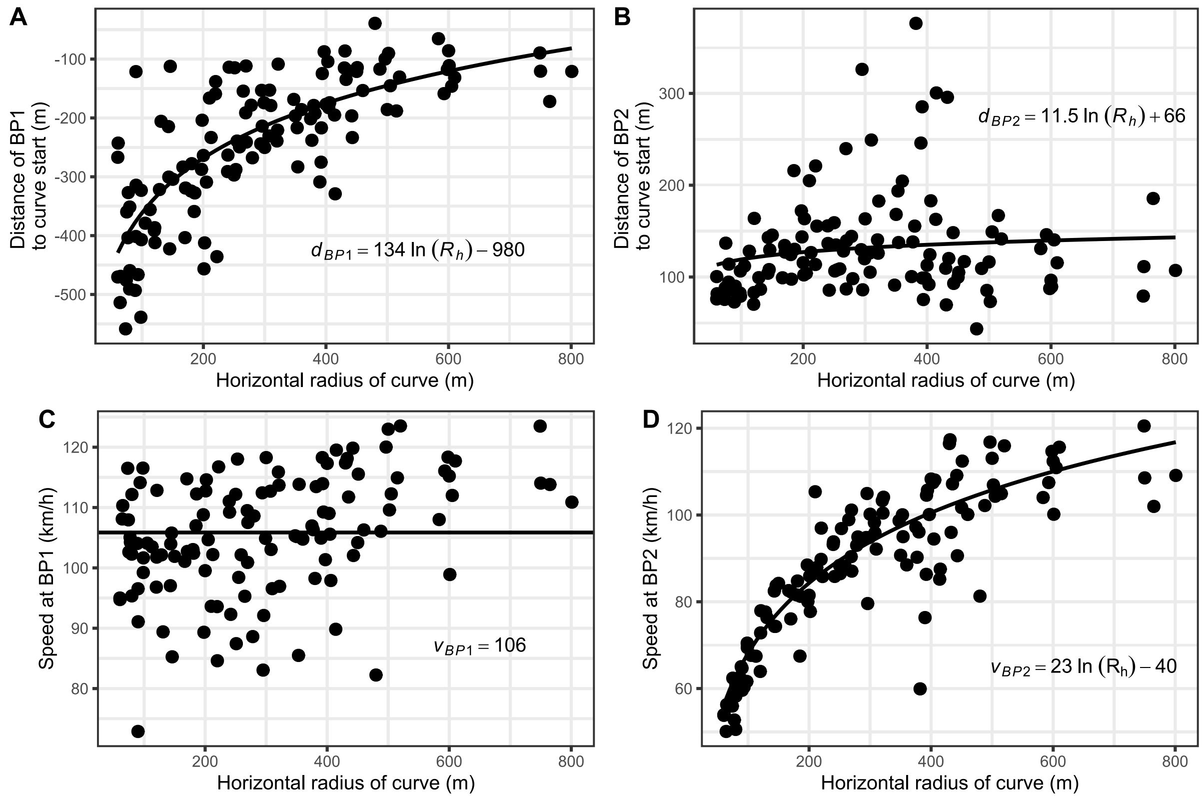


Figure 3-8 Relations of the positions and speeds at BP1 and BP2 to the horizontal radius of the curve. Each point refers to the average value of a single curve for that variable.

The formulas derived in Figure 3-8 contribute to the prediction of the position and speed of BP1 and BP2 (respectively d_{BP1} and d_{BP2} in meters and v_{BP1} and v_{BP2} in km/h) for different horizontal curve radii (R_h) in meters. These formulas have been used to create mean speed profiles for an array of different horizontal radii as shown in Figure 3-9. This shows the average speed behaviour in curve approach as a function of the horizontal radius of the curve, based on BP1 and BP2.

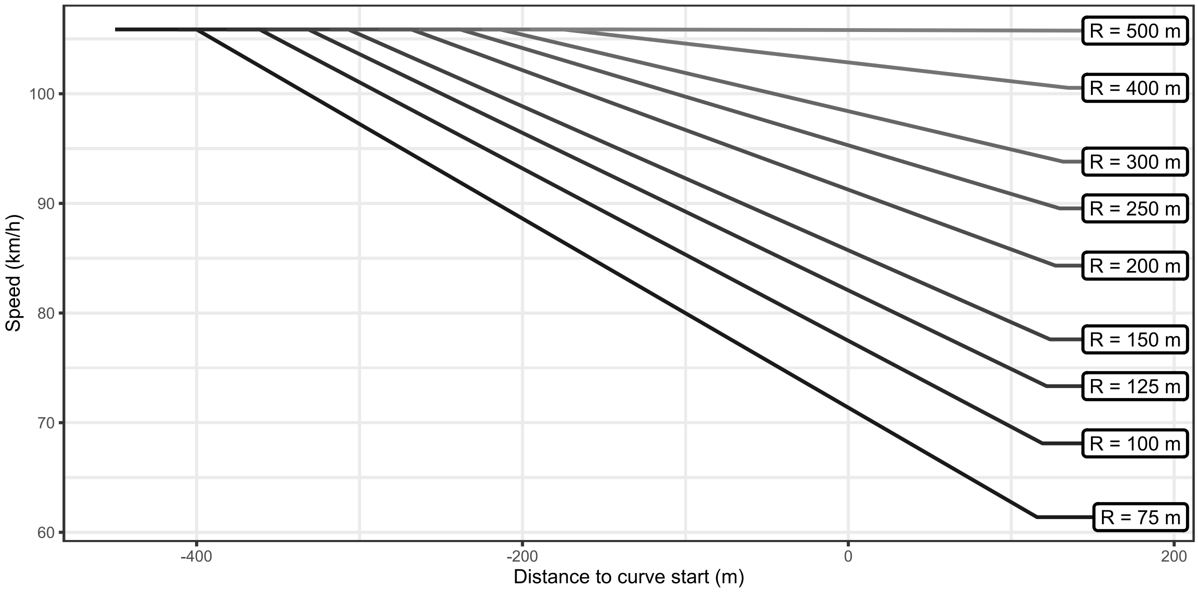


Figure 3-9 Mean speed profiles for different horizontal radii, based on the mean positions and speeds at BP1 and BP2, derived from Figure 3-8.

Each of the two breakpoints (BP1, BP2) shown as a mean in Figure 3-9 has a variability in the relation to the horizontal radius as shown in Figure 3-8. We have used linear regression analysis on all available variables, to investigate how much each variable explains the variability of BP1 and BP2. We used the BIC value as an indicator for the fitness of the model. We started with a base model, showing the breakpoint as a function of the horizontal radius of the curve, as shown in Figure 3-8. Next we created new models, in which we added one variable per model, to examine the contribution of this variable to explaining the variability. The added variables which lowered the BIC value of the base model by at least 0.05% showed that these variables could have a relevant contribution in explaining the variance of the breakpoints. Those variables were then checked for collinearity, before creating and testing multiple regression models. The outcome of these steps are presented in the next sub-sections.

3.3.3.1 Breakpoint 1 (BP1)

In Table 3-1 we show which variables contribute to predicting the distance of BP1 to curve start (d_{BP1}). Both the visible angle of the curve at BP1 ($v\varnothing_{BP1}$) and the visible length of the curve at BP1 (vLc_{BP1}) decrease the BIC value more than 2.9%, but are rather correlated, because the deflection angle is a derivative of curve radius and length. Because the closer a driver gets to a curve, the more length and deflection angle he can see, it is logical that the visible angle ($v\varnothing_{BP1}$) is related to the position of BP1 (d_{BP1}). We chose to investigate the effect of the visible angle ($v\varnothing_{BP1}$) further because it was found to decrease the BIC value more than the visible length of the curve, and is less obviously related to the distance of BP1 to the curve start. Next, the speed at BP1 (v_{BP1}) was found to explain some of the variability in the distance of BP1 to curve start. This is because the faster a driver drives, the more length they need to decelerate. Both the road sight distance and stopping sight distance at BP1 (RSD_{BP1} and SSD_{BP1}) improve the explainability of the model, but since both sight distances are collinear, only one of the two variables will be considered. We explored the stopping sight distance (SSD_{BP1}) further because it decreased the BIC value most and is an internationally used measurement. The total number of lanes and the number of pre-sorting lanes to the curve, as well as the width of the carriageway at BP1 (nL_{BP1}, nuL_{BP1}, and W_{BP1}) are also correlated. We explored the total number of lanes (nL_{BP1}) further, because it reduced the BIC value most. The effect of not having all the lanes available because of pre-sorting at BP1, is covered in a variable checking the presence of a discontinuity. The presence of different types of discontinuities (weaving section, exit lane or a fork) at BP1 (Ws_{BP1}, El_{BP1} and Fo_{BP1} respectively) are correlated, so we chose to explore the variable of continuity at BP1 (C_{BP1}) further, because it lowers the BIC value most and covers the presence of discontinuity and the need for pre-sorting as well.

Table 3-1 Variables which increase the explainability of the position of BP1 (grey variables are not explored further because of collinearity).

Added variable to $d_{BP1} = ln(R_h) + ...$	**Variable Interpretation**	**model BIC**	**BIC decrease**	**Variable collinear with**
$vØ_{BP1}$	Visible angle of the curve at BP1 (grad) (see Vos et al. (2021a))	19339426	2.97 %	vLc_{BP1} (R(1481780) = .49, p < .0001)
vLc_{BP1}	Visible Length of the curve at BP1 (m)	19349040	2.92 %	$Øv_{BP1}$ (R(1481780) = .49, p < .0001)
v_{BP1}	Speed at BP1 (km/h)	19457787	2.37 %	
SSD_{BP1}	Stopping Sight Distance at BP1 (m)	19605067	1.64 %	RSD_{BP1} (R(1481903) = -.86, p < .0001)
RSD_{BP1}	Road Sight Distance at BP1 (m)	19632363	1.50 %	SSD_{BP1} (R(1481903) = -.86, p < .0001)
nL_{BP1}	Number of Lanes at BP1	19798294	0.67 %	nuL_{BP1} (R(1481903) = -.68, p < .0001), W_{BP1} (R(1481903) = -.75, p < .0001),
W_{BP1}	Width of carriageway at BP1	19844715	0.43 %	nL_{BP1} (R(1481903) = -.75, p < .0001), nuL_{BP1} (R(1481903) = -.47, p < .0001)
C_{BP1}	Continuity at BP1 (1 = continuous, 0 = discontinuous)	19863030	0.34 %	Fo_{BP1} (R(1481903) = -.47, p < .0001), El_{BP1} R(1481903) = -.41, p < .0001), Ws_{BP1} R(1481903) = -.49, p < .0001)
CSS_{BP1}	Curve Sign in Sight at breakpoint 1 (1 = yes, 0 = no)	19872820	0.29 %	
Ws_{BP1}	Weaving section at breakpoint 1 (1 = weaving section, 0 = continuous or other discontinuity)	19888209	0.21 %	C_{BP1} (R(1481903) = -.49, p < .0001)
$SDmax_{BP1}$	Maximum Sight Distance at BP1 (m) (maximum of sight on road, stopping sight, guardrail, curve signs, treeline or closed elements	19895226	0.18 %	
nuL_{BP1}	Number of usable Lanes at breakpoint 1 based on pre-sorting; correct pre-sorting lanes leading up to the curve	19898082	0.17 %	nL_{BP1} (R(1481903) = -.68, p < .0001), W_{BP1} (R(1481903) = -.47, p < .0001)
El_{BP1}	Exit lane at breakpoint 1 (1 = exit lane, 0 = continuous or other discontinuity)	19898961	0.16 %	C_{BP1} (R(1481903) = -.41, p < .0001)
Fo_{BP1}	fork at breakpoint 1 ((1 = fork, 0 = continuous or other discontinuity)	19911603	0.10 %	C_{BP1} (R(1481903) = -.47, p < .0001)
T	Daytime (1 = sun up, 0 = sun down)	19916198	0.07 %	

The selected variables in Table 3-1 were used to create multiple regression models for predicting the position of BP1. The results are shown in Table 3-2. This shows the added explainability of using sight and visibility in the model to predict the distance of BP1. Dropping the visible angle ($v\O_{BP1}$) from the model, decreases the explainability drastically as seen in models 4 and 7 in Table 3-2. The models show that with more curve angle visible, the position of BP1 moves closer towards the curve start. But, with more sight distance (SSD_{BP1} and $SDmax_{BP1}$) available at BP1, this is located further away from the curve start. However, a sight on curve signs (CSS_{BP1}) decreases the distance of BP1 to the curve start. Figure 3-10 shows how these sight distances interact with the position of BP1. Stopping Sight Distance from BP1 (SSD_{BP1}) is defined by how far ahead the driver is able to see a braking light. In most cases the SSD remains the roughly same if the position of BP1 changes. Whether or not a curve sign is visible from BP1 (CSS_{BP1}) is defined by whether or not BP1 is positoned beyond the point where the signs are visible the first time. If BP1 gets closer to the curve start from that point, the varible remains "yes". The visible part of deflection angle seen from BP1 ($v\O_{BP1}$) is very much related to the position of BP1 to the curve start. The closer BP1 is located to the curve start, the larger the visible deflection angle will be. Adding lanes (nL_{BP1}) to the cross section, increases the distance between BP1 and the curve start, and this is even more when a discontinuity (C_{BP1}) is added. Finally, during daytime (T) the position of BP1 is located closer to the curve start, than during night time.

Table 3-2 Regression analysis results for the position of BP1.

	Model 1 (base)	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	-980.286***	-1104.617***	-1115.862***	-934.521***	-965.670***	-947.848***	-495.498***
	(1.629)	(1.166)	(1.235)	(1.586)	(1.299)	(1.263)	(1.481)
$ln(R_h)$	134.395***	180.308***	182.810***	138.395***	192.028***	191.076***	155.613***
	(0.289)	(0.194)	(0.202)	(0.278)	(0.197)	(0.196)	(0.236)
$v\O_{BP1}$		2.852***	2.829***		2.448***	2.449***	
		(0.002)	(0.003)		(0.003)	(0.003)	
v_{BP1}					-2.269***	-2.308***	-4.166***
					(0.006)	(0.006)	(0.008)
SSD_{BP1}		-0.826***	-0.792***		-0.650***	-0.650***	-0.457***
		(0.001)	(0.001)		(0.001)	(0.001)	(0.001)
$SDmax_{BP1}$			-0.043***		-0.038***	-0.038***	-0.027***
			(0.000)		(0.000)	(0.000)	(0.000)
CSS_{BP1}			19.756***		21.669***	21.010***	
			(0.276)		(0.264)	(0.264)	
nL_{BP1}				-42.137***	-3.798***	-4.366***	-14.986***
				(0.147)	(0.101)	(0.100)	(0.128)
C_{BP1}				48.093***	14.982***	13.978***	43.465***
				(0.386)	(0.253)	(0.253)	(0.322)
T					12.004***		11.344***
					(0.209)		(0.268)
Num.Obs.	1481905	1481905	1481905	1481905	1481905	1481905	1481905
R2	0.127	0.629	0.635	0.210	0.669	0.668	0.457
R2 Adj.	0.127	0.629	0.635	0.210	0.669	0.668	0.457
AIC	19931003.8	18664030.3	18640587.0	19782830.0	18493508.1	18496798.2	19227773.9
BIC	19931040.4	18664091.3	18640672.5	19782891.1	18493642.4	18496920.3	19227883.8
Log.Lik.	-9965498.884	-9332010.129	-9320286.511	-9891410.008	-9246743.040	-9248389.087	-9613877.949
F	215655.159	836516.766	514640.655	131390.746	332926.431	373300.302	178081.226

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$;

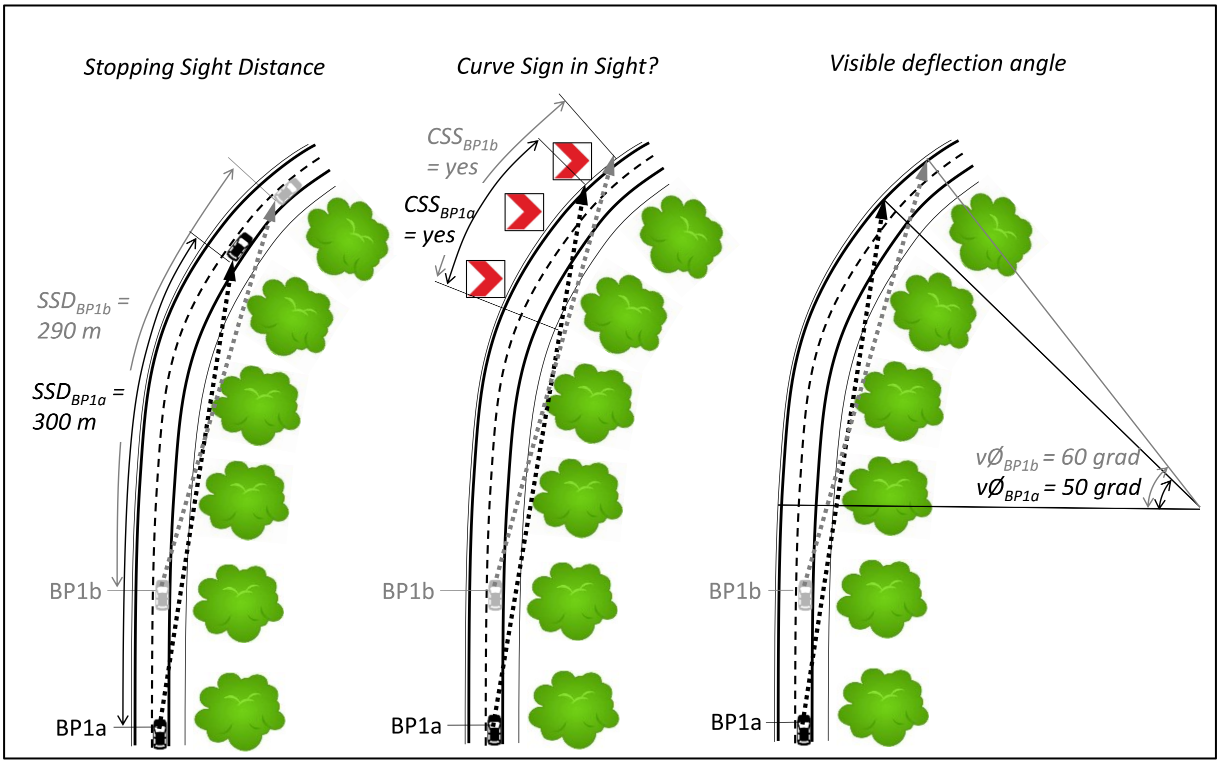


Figure 3-10 Sightlines from BP1 are shown in two different positions of BP1 (a and b) as a dotted arrow to show the effect on different sight distance measurements.

The speed at BP1 (v_{BP1}) is not correlated with the curve itself, but is used as a variable to define the position of BP1. So, no specific model has been created to define the speed at BP1. In case of consecutive curves, the speed at BP2 (v_{BP2}) for the first curve, can be used as the speed at BP1 (v_{BP1}) to predict the position of BP1 (d_{BP1}) for the second curve.

3.3.3.2 Breakpoint 2 (BP2)

As shown in Figure 3-8B, the position of BP2 (d_{BP2}) is weakly correlated with the horizontal radius of the curve. The position is on average 135 meters from the curve start, but varies between 50 and 350 meters. Figure 3-7 shows no variables correlate to the position of BP2. We found that different variables did not reduce the BIC by more than 0.15% compared to the base model. Curve length has no influence in this, since the curves in this study have an average length of 303 m (sd=46.5 m). When investigating the curves which are causing the variability, we notice that the curves which have a position of BP2 beyond 160 meter after curve start, all have follow-up curves which need further speed reduction. We can exclude these curves in our analysis on the position of BP2, since these positions are actually related to the consecutive curve. Hence we assume the position where drivers stop decelerating (d_{BP2}) is rather constant along different horizontal radii.

In Table 3-3 we show the variables added to the base model which contribute to the prediction of the speed at BP2. The speed at BP1 decreases the BIC of the base model most. Since the deflection angle of the curve and the entry transition curve ($Ø_c$ and $Ø_{etc}$, respectively) as well as the Curvature Change Rate (CCR_{tot}) are collinear with the total deflection angle ($Ø_{tot}$) we chose to explore this variable further. By doing so, we isolated the deflection angle, which is part of the calculation of the CCR. Also the total length of the curve (L_{tot}) and turning direction (*Dir*) are of influence. In the cross section, the presence of a discontinuity, number of lanes and the width of the emergency lane (C_{BP2}, nL and W_{el}) further lower the BIC. Finally, the presence of curve signs (*pCS*) also lowers the BIC of the base model.

Table 3-3 Variables which increase the explainability of the speed at BP2 (grey variables are not explored further because of collinearity).

Added variable to $v_{BP2} = ln(R_h) +$ ...	Variable Interpretation	model BIC	BIC decrease	Variable collinear with
v_{BP1}	Speed at BP1 (km/h)	12049030	1.96 %	
$Ø_c$	Deflection angle of the horizontal curve (rad)	12269707	0.17 %	$Ø_{tot}$ (R(1481903) = .98, p < .0001) CCR_c (R(1481903) = .63, p < .0001)
$Ø_{tot}$	Total deflection angle of the horizontal curve, including transition curves (rad)	12269917	0.16 %	$Ø_{etc}$ (R(1481903) = .83, p < .0001) $Ø_c$ (R(1481903) = .98, p < .0001) CCR_{tot} (R(1481903) = .80, p < .0001)
L_{tot}	Total Length of the horizontal curve, including transition curves (m)	12272569	0.14 %	L_c (R(1481903) = .94, p < .0001)
C_{BP2}	Continuity at BP2 (1 = continuous, 0 = discontinuous)	12274609	0.13 %	
nL	number of Lanes in curve	12274036	0.13 %	W (R(1481903) = .74, p < .0001)
CCR_{tot}	Total Curvature Change Rate of horizontal curve, including transition curves	12276095	0.11 %	CCR_c (R(1481903) = .98, p < .0001) $Ø_{tot}$ (R(1481903) = .80, p < .0001)
Dir	Direction of curve (1 = right turning, -1 = left turning))	12276473	0.11 %	i (R(1481903) = .78, p < .0001)
CCR_c	Curvature Change Rate of horizontal curve	12277515	0.10 %	CCR_{tot} (R(1481903) = .98, p < .0001) $Ø_c$ (R(1481903) = .63, p < .0001)
$Ø_{etc}$	Deflection angle of entry transition curve (rad)	12278122	0.10 %	$Ø_{tot}$ (R(1481903) = .83, p < .0001)
W	Width of carriageway in curve (m)	12277702	0.10 %	nL (R(1481903) = .74, p < .0001)
L_c	Length of horizontal curve (m)	12279619	0.09 %	L_{tot} (R(1481903) = .94, p < .0001)
L_{etc}	Length of entry transition curve (m)	12279271	0.09 %	A_{etc} R(1481903) = .77, p < .0001)
i	Superelevation in curve (%)	12281303	0.07 %	Dir (R(1481903) = .78, p < .0001)
W_{el}	Width of emergency lane (m)	12283065	0.06 %	
A_{etc}	A-value of entry transition curve (clothoid parameter)	12283939	0.05 %	L_{etc} R(1481903) = .77, p < .0001)
pCS	Presence of curve signs in curve (1 = yes, 0 = no)	12283822	0.05 %	

The selected variables in Table 3-3 were used to create multiple regression models. The results are shown in Table 3-4. This shows that with a higher speed in front of the curve (v_{BP1}), a higher speed in the curve (v_{BP2}) is obtained. Furthermore, increasing length and angle of the curve ($Ø_{tot}$ and L_{tot}) seem to increase the speed in a curve. And, also, the wider the cross section gets, the higher the speed gets. However, adding the speed at BP1, deflection angle, length and direction of the curve (v_{BP1}, $Ø_{tot,}$, L_{tot} and Dir) to the model, nullifies this effect for the number of lanes in the curve (nL).

Table 3-4 Regression analysis results for the speed at BP2.

	Model 1 (base)	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Constant	-39.609***	-54.003***	-48.737***	-60.448***	-37.843***	-43.345***	-45.276***
	(0.124)	(0.130)	(0.135)	(0.124)	(0.140)	(0.147)	(0.160)
$ln(R_h)$	23.391***	19.770***	18.124***	21.041***	22.386***	17.458***	17.804***
	(0.022)	(0.022)	(0.025)	(0.021)	(0.023)	(0.025)	(0.028)
v_{BP1}		0.331***	0.337***	0.318***		0.353***	0.351***
		(0.001)	(0.001)	(0.001)		(0.001)	(0.001)
$Ø_{tot}$		0.020***	0.040***			0.038***	0.039***
		(0.000)	(0.000)			(0.000)	(0.000)
L_{tot}			0.006***	0.002***		0.008***	0.008***
			(0.000)	(0.000)		(0.000)	(0.000)
Dir			3.385***	-1.214***		3.222***	3.333***
			(0.026)	(0.014)		(0.026)	(0.026)
nL					1.869***	-0.234***	-0.307***
					(0.018)	(0.017)	(0.017)
C_{BP2}					-4.531***	-9.227***	-9.229***
					(0.044)	(0.041)	(0.041)
W_{el}					1.429***	1.236***	1.240***
					(0.017)	(0.016)	(0.016)
pCS							0.913***
							(0.030)
Num.Obs.	1481905	1481905	1481905	1481905	1481905	1481905	1481905
R2	0.433	0.531	0.536	0.523	0.446	0.554	0.554
R2 Adj.	0.433	0.531	0.536	0.523	0.446	0.554	0.554
AIC	12290097.4	12010287.7	11992963.6	12034897.2	12256647.7	11935478.1	11934563.4
BIC	12290134.1	12010348.7	11993049.1	12034970.5	12256720.9	11935600.2	11934697.7
Log.Lik.	-6145045.720	-6005138.838	-5996474.811	-6017442.606	-6128317.830	-5967729.064	-5967270.703
F	1133386.776	558968.079	342810.984	406220.801	298274.797	230059.611	204725.726

* p < 0.1, ** p < 0.05, *** p < 0.01

3.4 Discussion, limitations and future research directions

We have shown that the radius of a curve is of influence on the position where drivers start to decelerate in front of a curve, as well as the speed they select within a curve. We present a relation which shows when the horizontal radius decreases, drivers start decelerating further away from the curve. This deviates from the findings by Alfonso Montella et al. (2015), who show drivers start decelerating closer to the curve, when the radius decreases. This difference might be explained by the use of a driving simulator in the study by Alfonso Montella et al. (2015) and the distortion of a curve from a driver's standpoint (Brummelaar, 1975) in such an experiment. This strengthens the hypothesis that drivers on freeways use other cues besides the horizontal radius alone to select their speed.

This research focusses on the positions where 0 m/s^2 was reached in speed profiles. These positions however do not match up with the perceptual tasks, since the breakpoints are preceded by the cognitive and psychomotor tasks (Campbell et al., 2012; Shinar, 2017c). The cues drivers actually react to, could be present up to a couple of seconds before the position where 0 m/s^2 is reached.

The amount of visibility of the curve at BP1 is correlated with the position of BP1. It remains unclear however whether this is a cause or an effect, because the closer BP1 is positioned to the curve start, the more of that curve the driver would be able to see. So, visibility-variables which take the position of the curve start into account (e.g. visible angle or curve sign in sight) should not be taken into account in explaining the position of BP1. This means that the need to recognise 100 meters of the curve (Campbell et al., 2012; Rijkswaterstaat, 2022) cannot be underpinned by this study. The focus should be on the sight distances though, which show that if a driver has increased sight distances available, deceleration occurs earlier. Effects of individual guiding elements were not found, although adding guiding elements to the sight distance ($SDmax_{BP1}$) increases this effect. The finding that stopping sight distance (SSD_{BP1}) added more explainability to the regression analysis of the position of BP1 (d_{BP1}) than the road sight distance (RSD_{BP1}) could be explained because *SSD* analysis in 'Zicht' created a smoother line than *RSD* analysis because it is less prone to sight obstructions. This adds to the thought that drivers need continuous information (Coutton-Jean et al., 2009; Singh & Fulvio, 2007). The presence of curve signs only correlates to the position of BP1, when these are tested on correlation in Figure 3-7. But when added in a regression model together with horizontal radius it shows no extra explainability, other than the speed at BP2 (v_{BP2}).

The cross section is of influence both on the position where deceleration starts (BP1), as well as the speed in a curve. Increasing the width of a cross section, increases the distance of BP1 from the curve start. This could be explained by the speed at BP1, however this was not collinear. One explanation could be the extra perceived risk with multiple lanes in a cross section (Vos et al., 2021a), which could lead the driver to decelerate more cautiously. But, because we tested only speed profiles in free flow situations, this explanation is unlikely, since not much other vehicles should be around during the measurement. The addition of pre-sorting tasks effects increase this effect. Having a discontinuity at breakpoint 1, increases the distance to the curve start even more. The speed in a curve decreases with the addition of extra lanes, but only if the length and angle of the curve are taken into account. When analysing the number of lanes in a curve without any other variables, the increasing number of lanes increases speed in a curve, just as Calvi et al. (2018) also showed. Our study shows the impact of other variables of the curve on this effect. One of these effects is the direction of the curve. We show that in right turning curves the speed is higher than in left turning curves, which is not in line with the findings of Farah et al. (2019) but is in line with findings of Misaghi and Hassan (2005). Since more visual attention is towards the right in right turning curves compared to attention to the left in left turning curves (Lappi & Lehtonen, 2013; Shinar et al., 1977), but no sight distances added explainability to the speed at breakpoint 2, it remains unclear as to why drivers drive faster in right turning curves. However, since all the afore mentioned studies were undertaken in right driving countries, it could have to do with the added visibility of the curve trajectory, because it is less obscured by the bodywork of the car.

The relation between the radius and start of deceleration shows an increase in variability of the position of BP1 when the radius decreases. This heteroscedasticity is explained mostly by the speed at BP1, the larger the radius of a curve, the less speed adjustment is needed. The relation of radius and the speed in a curve shows a decrease in variability of the speed at BP2 if the radius decreases. This shows that the smaller a radius gets, the less speed in a curve is influenced by other variables than the horizontal radius.

By using all individual speed profiles in the statistical analysis, we were able to gain insight in individual speed choices. This showed a positive correlation between the speed before a curve, and inside a curve, suggesting that fast drivers on tangents, also drive fast through curves. This could relate to individual driving style or familiarity. Since speed before a curve is important to the speed in a curve, speed prediction models should pay more attention to elements which influence speed before a curve, such as discontinuities. Hassan, Sarhan, and Dimaiuta (2011) already noted that both upstream and downstream elements influence measurements at a certain location.

No correlation to the vertical alignment was found in this study. This could be related to the relatively large sag curves in the data-set, so critical combinations are almost not present in the data. This could also be due to the relative flatness of most road sections in the Netherlands, which could also explain why the grade of the road did not correlate with any breakpoint as well.

The amount of precipitation has no substantial influence on the position of BP1, or the speed at BP2, and therefore not on deceleration. Wet surfaces offer less friction (Donnell et al., 2016; Li & He, 2016) and therefore lead to increased crash risks. This increased risk seems not to influence speed behaviour. A small correlation to daylight and breakpoint 1 is seen. Drivers tend start decelerating later in daylight, suggesting a more cautious curve approach in lessened visibility, the effect is however less than half a second.

The sample of drivers used in this research appear to be faster drivers than the average driver in the Netherlands. This might also indicate a higher level of experience and familiarity, and could also be an explanation for not finding relations to precipitation. This should be kept in mind when translating these insights into design-policy or safety assessments. The use of this set of faster drivers represents a subset which is willing to take a higher risk of skidding than the average driver.

The use of High Frequency Floating Car data is promising, but this data is not readily available because regular Floating Car Data recording methods need to be altered into a higher data gathering frequency within the used apps. This includes careful consideration of research purposes and selecting useful road sections in future research using this type of data. Because the data has high frequency time series, using complex functional data analysis could give more multi-dimensional insights (Ramsay, Hooker, & Graves, 2009).

The discussion showed uncertainty in causality for the relation between visibility and the position where drivers start decelerating. Further research on where the visual focus of drivers lies just before deceleration, could give better insights into the cues which drivers use to start decelerating. Using two time dependent variables – visual focus and start of deceleration – could infer a causal relation between the guiding element which was focussed on by the driver and the deceleration which occurred, using knowledge about the drivers information processing (Shinar, 2017c).

3.5 Conclusions

We were able to show that the distance to a curve start where drivers start to decelerate is related to the horizontal radius of that curve, and this result confirms earlier findings that speed in the curve is also related to the horizontal radius. We found relations of the driven speed in front of the curve to the speed behaviour in curve approach and concluded that drivers stop decelerating at around 135 meters into the curve independent from the horizontal radius and speed.

So, horizontal radius is a key characteristic for a curve and the speed behaviour upon curve entry. Variability in positions where drivers start to decelerate are explained further by stopping sight distances, number of lanes, the presence of a discontinuity for pre-sorting and daylight. We were unable to find relations towards specific guiding elements in a curve which determine speed behaviour in front of a curve, other than the presence of curve signs.

The speed in a curve is further explained by the deflection angle and length of a curve, as well as the direction of the curve. Also the cross section is of influence, but we were unable to provide good explanation to the relation of the number of lanes, width of the emergency lane and discontinuities with the speed inside the curve. Of further interest is that sight distances do not seem to influence speed within a curve.

Given the insights gained in this research, freeway curve design should not be solely based on side friction, but should take actual speed behaviour into account as well. This means considering the existence of deceleration in a constant circular curve, and acknowledging the influence of upstream road characteristics and other curve characteristics on speed behaviour upon a curve. This could reveal differences in friction demand based on actual speed behaviour. Furthermore, problems regarding to speeding and traffic safety in curves, can be analysed using the variables in this research.

4 Parsimonious Models of the 85^{th} Percentile Speed Development through Curves

This chapter has previously been published as: ***Vos, J.**, & Farah, H. (2022). Speed development at freeway curves based on high frequency floating car data. European Journal of Transport and Infrastructure Research, 22(2), 201-223.*

Abstract

Road designers need to have insights where deceleration and acceleration are expected related to the position of the curve, and in in which amount so that drivers are able to safely decelerate and accelerate respectively into and out of a freeway curve. For this, empirical speed data is needed. Therefore, Floating Car Data in 153 curves in The Netherlands were collected at a resolution of 1 Hz and were filtered on free-flow periods, to analyse over 800 thousand unique continuous free-flow speed observations on these curves. Regression models were developed to predict speed development, including deceleration and acceleration behaviour upon entering and exiting freeway curves. The models rely on easy to generate geometric design variables, including the start and end position of the horizontal curve, the horizontal radius and the number of lanes. Using these variables, the designer can predict the speed development based on the 85^{th} percentile of speed and acceleration, relative to the position of the curve. The regression models reveal strong goodness-of-fit of the predicted 85^{th} percentiles of speed in a curve, showing acceleration and deceleration inside the curve, and higher predicted 85^{th} percentile speeds than the design speeds. The models also show satisfying results in speed development prediction in sets of consecutive curves with different characteristics, as well as deceleration when entering a first curve and acceleration when exiting a last curve. These insights are valuable in evaluating road design in relation to traffic safety based on its predicted use.

4.1 Introduction

Curves are known as an infrastructural element where many road accidents occur (Davidse et al., 2020). If a curve comes unexpectedly, drivers might be surprised (Alexander & Lunenfeld, 1986; Richard & Lichty, 2013) and react by braking too fiercely resulting in large speed differences in traffic or a skidding car and run-of-the-road accidents (Aarts & Van Schagen, 2006; Mahapatra & Kumar, 2018; Torbic et al., 2014). Drivers should be able to safely decelerate and accelerate respectively into and out of a freeway curve. Therefore designers need to have insights in where deceleration and acceleration are expected related to the position of the curve, and in in which amount. This will help designers to design safe deceleration and accelerations lanes, so the driver can give the needed attention to the operational driving task at hand; speed adjustment. It will furthermore give insights into the smoothness of speed adjustment in consecutive curves, leading to a consistent design without surprising the driver (Hassan, 2004).

Traditionally, speed prediction modelling use point speed data, but it has been argued that this method does not show enough insights into acceleration and deceleration (Hassan, Sarhan, & Dimaiuta, 2011). Continuous speed profiles however do provide valuable insights into speed development along curves (Dias et al., 2018), because they provide continuous information along the alignment. In the last decade several studies have generated speed profiles using driving simulators (Bella, 2014; Montella, Galante, et al., 2014; Alfonso Montella et al., 2015; Wang et al., 2020), usually to research specific elements of the road (Bobermin et al., 2021). Other studies used instrumented vehicles to analyse speed profiles (Altamira, García Ramírez, Echaveguren, & Marcet, 2014; Cafiso & Cerni, 2012; Cafiso & La Cava, 2009; Echaveguren, Henríquez, & Jiménez-Ramos, 2020; Hashim, Abdel-Wahed, & Moustafa, 2016; Malaghan, Pawar, & Dia, 2020, 2021; Montella, Pariota, Galante, Imbriani, & Mauriello, 2014; Nama, Sil, Maurya, & Maji, 2020). These methods usually have low sample sizes of observed curves or participants and suffer from participant bias. Furthermore, besides the study of Alfonso Montella et al. (2015), these studies focus on the amount of deceleration or acceleration, but not on where this is located related to the position of the curve. Figure 4-1 shows the general approach and the used variables in recent literature. Usually, the minimum speed in the curve (v_{min}) is identified and subtracted from the maximum speed upstream of the curve (v_{max}). This results in the speed difference known as Δv. The distance between the positions of v_{max} and v_{min} (D) is then used to calculate the deceleration (d) using equation 4-1.

$$d = \frac{(v_{max} - v_{min})}{2D} = \frac{\Delta v}{2D} \qquad [4\text{-}1]$$

where:

d	=	average deceleration
v_{max}	=	maximum measured speed upstream of curve
v_{min}	=	minimum measured speed inside curve
Δv	=	the difference between v_{max} and v_{min}
D	=	distance between positions of v_{max} and v_{min}

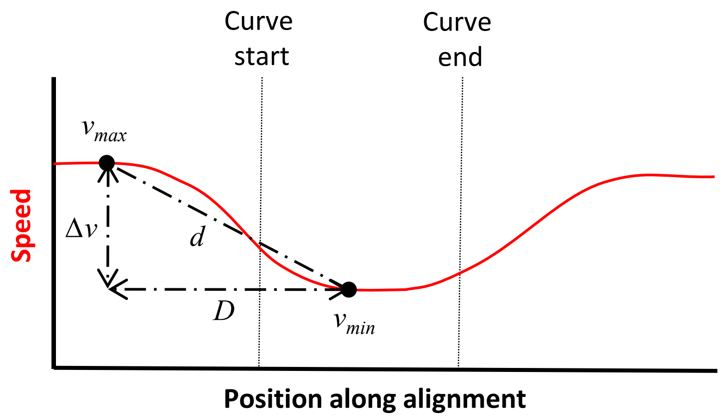


Figure 4-1 Overview of general approach and variables used in recent deceleration research.

This approach has two drawbacks. It does not generate a model to position the deceleration related to the position of the curve, and it assumes a constant deceleration. Several studies have shown that v_{min} is not reached at curve start, otherwise known as the Point of Curvature (*PC*), or at the Midpoint of the Curve (*MC*) (Bella, 2014; Malaghan et al., 2021; Vos, Farah, & Hagenzieker, 2021b). So, there seems to be no geometrically fixed point defining v_{min}. This makes it hard to implement speed profiles in geometric design checks and could underestimate the combined need for lateral and longitudinal friction during curve entry (Hassan, 2004). To summarize, previous research into speed profiles has improved our understanding of deceleration. However, there are still some limitations in existing speed profile research:

- low sample sizes;
- participant bias;
- inability to relate deceleration to position of curve;
- an assumption of constant deceleration based on Δv.

Therefore, we aim to further develop the understanding of speed behaviour and its implementation by developing speed and acceleration profiles. This research therefore has three goals:

1. model speed development related to the position of the curve as speed profiles;
2. model acceleration development related to the position of the curve as acceleration profiles;
3. use generic variables which are easy to derive from geometric designs and develop parsimonious models (Tenenbaum & Filho, 2016).

To overcome the low sample sizes and participant bias, High Frequency Floating Car Data (HF FCD) is used. This is speed data collected from a route navigation app users which was for our study set to a data sampling frequency of 1 Hz. This approach ensures naturalistic driving, because the users of the app were unaware of the data collection. The only downside is that the users remain completely anonymous, because of General Data Protection Regulation laws, so no demographics are known. Besides this downside, this data collection provides thousands of unique speed profiles in a large number of curves.

To our knowledge, this study is the first to use HF FCD to analyse speed profiles and generate models to predict deceleration and acceleration related to the position of the curve.

The following section further discusses the methods. The third section analyses the retrieved data in two parts; first it analyses the speed development, followed by the acceleration development. In the fourth section we discuss the results and the study limitations. Finally, we summarize the main conclusions in section five.

4.2 Methods

For the analysis in this study, 99 freeway sections in The Netherlands were selected, containing 153 curves with different characteristics, as shown in Table 1. The freeway sections were chosen with upstream and downstream tangents of at least 1.000 m, which ensure that drivers are able to drive their desired operating speed in free flow situations. The curves are located throughout The Netherlands – both in rural and urban areas – as shown in Figure 4-2, and only contain main carriageways and connector roads in junctions. The selected curves include long tangents upstream and downstream which ensure that drivers' speed behaviours are not influenced by other geometric elements such as small tangents, or cross roads.

Figure 4-2 Map of The Netherlands showing the selected freeway sections.

All selected road sections in this study were re-engineered based on digital terrain models to obtain the present geometrical characteristics. The main horizontal characteristics are summarised in Table 1. Since The Netherlands is a rather flat country, the range of the vertical grades of the curves is -3.3% – +2.8% (average 0.0%, SD = 1.1%).

4.2.1 High Frequency Floating Car Data

High Frequency Floating Car Data (HF FCD) was collected by setting the data collection frequency of the route navigation app "Flitsmeister" to 1 Hz along the selected freeway sections. This smartphone app is used by approximately 1.6 million users in The Netherlands – roughly 15% of all driver-licence holders. Data was collected in March, April and September of 2020, generating 12.5 million individual speed profiles. These were bought by the Dutch Ministry of Infrastructure.

The HF FCD was then mapped along the re-engineered freeway sections, to generate individual speed and acceleration profiles, which are connected to the geometric characteristics of the respective road sections.

In these individual speed profiles, breakpoints (BPs) were identified. These BPs are the positions surrounding curve start and curve end where drivers deviate from a constant speed (Alfonso Montella et al., 2015; Vos et al., 2021b). These BPs are defined based on the position where drivers first deviate from 0 m/s^2 upstream of curve start (BP1), first reset to 0 m/s^2 downstream of curve start (BP2), first deviate from 0 m/s^2 upstream of a curve end (BP3), and first reset to 0 m/s^2 downstream of a curve end (BP4). Furthermore, we defined the positions where maximum deceleration occurs upstream of curve start (MAXdec) and where the maximum acceleration occurs downstream of curve end (MAXacc). This is shown in Figure 4-3, in theoretical speed and acceleration profiles. Curve start and curve end are therefore the reference points (i.e, distance value of zero) of the BPs and are defined by the start and end of the continuous radius. Relative to these reference points, upstream position values are negative and downstream position values are positive. At those positions, the speed and deceleration are captured for the models in this research.

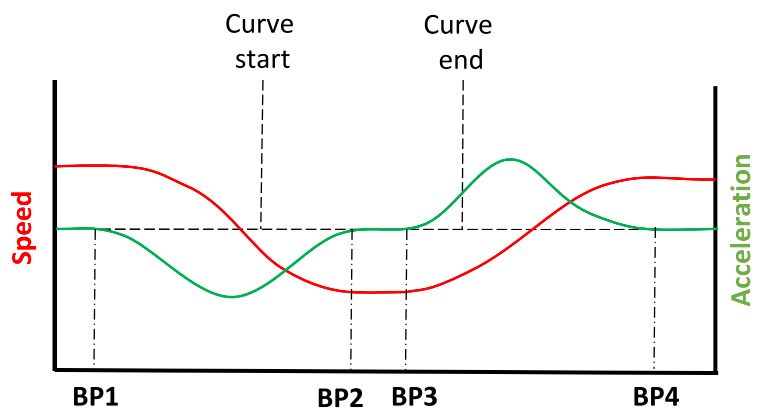


Figure 4-3 Theoretical speed and acceleration profiles, showing the positions of the breakpoints and maximum deceleration and acceleration in relation to curve start and curve end.

4.2.2 Data filtering and curve grouping

Individual speed profiles during road works and in non free-flow situations were filtered out, because these speed observations could be affected by other factors other than the road geometrics. Furthermore, v85 is usually defined as the speed which 85 percent of all vehicles are observed to travel at or below in free-flowing conditions (Hassan, Sarhan, Porter, et al., 2011; Lamm, Choueiri, Hayward, & Paluri, 1988). For simplicity we will refer to the 85th percentile of the free flow measurements as 85th percentile speeds or v85. To identify free-flow observations, detector loop data (Nationaal Dataportaal Wegverkeer, 2020) was used from each freeway section which shows the total amount of traffic per minute per lane. Based on the timestamps of the HF FCD, we eliminated all individual speed profiles in periods with more than 5 vehicles per minute per lane. This results in a 95% probability that the remaining individual speed observations were in free flow situation with headways greater than 5 seconds (Hashim, 2011). After filtering, the data included 881,153 individual speed profiles, with an average of 8,901 individual speed profiles per freeway section (max 39,618, min 330). This sample represents 7.6% off all drivers in the selected time periods (free-flow without roadworks). The loop-detectors also collect average speed per minute. The averages of the entire population from the loop-detectors were compared, to the speed observations from the HF FCD data sample and this has shown that the sample of drivers in the HF FCD drive on average 5.4 km/h (SD 4.9 km/h) faster than the entire population. Based on other speed observations of the entire population (Farah et al., 2019), the sample in this study represents on average around the 60th percentile of all drivers.

Because in the selected freeway sections several consecutive curves were included, the curves were grouped based on their relative positions. This was done to gain information about the speed and acceleration observations at the different BPs without it being influenced by other nearby consecutive curves. So, speed behaviour upstream of a curve was analysed on first curves only, speed inside a curve was analysed on single curves only and speed downstream of a curve was analysed on last curves only. Single curves are also included in the first and last curve groups, because it is assumed they have the same behaviour at respectively curve start and curve end. The variables for each curve group are summarised in Table 4-1.

Table 4-1 Summary of the curve groups.

	All curves	First curves	Single curves	Last curves
Number of curves	153	99	47	99
Average radius (m.)	297 range: 60 – 801 SD = 174	315 range: 60 – 801 SD = 189	301 range: 60 – 749 SD = 172	268 range: 60 – 750 SD = 167
Average length (m.)	303 range: 31 – 1018 SD = 210	308 range: 31 – 1018 SD = 223	432 range: 78 – 1018 SD = 212	338 range: 50 – 1018 SD = 212
Average deflection angle (grad.)	86 range: 6 – 284 SD = 67	85 range: 6 – 284 SD = 71	112 range: 36 – 284 SD = 65	103 range: 11 – 284 SD = 68
Mode of number of lanes	1 range: 1 – 4 SD = 0.8	1 range: 1 – 4 SD = 0.8	1 range: 1 – 3 SD = 0.7	1 range: 1 – 3 SD = 0.6

Based on these curve groups speed development was analysed first, followed by an analysis on acceleration development.

4.3 Data analysis

The focus of the analysis in this paper is on the 85th percentile of speed and acceleration because design speeds are determined based on the 85th percentile of speeds or anticipated operating speeds (Fitzpatrick & Kahl, 1992; *A Policy on Geometric Design of Highways and Streets 2018*, 2018; Rijkswaterstaat, 2022). Furthermore, the main design variable in a horizontal curve, is its horizontal radius which is known to be of main influence on driving speeds (Hassan, Sarhan, Porter, et al., 2011). Therefore, the speed analysis starts with analysing the 85th percentile of speeds at the different breakpoints and in relation to the horizontal radius.

4.3.1 Speed profiles based on the 85th percentile of speed

The 85th percentile of speeds at the four breakpoints of each curve in the dataset were calculated, but also at the curve start and curve end. The deceleration and acceleration inside the continuous curve is of special interest, because this could entail risks of skidding since this combines both the use of both lateral and longitudinal friction (Himes et al., 2019; Pacejka & Besselink, 2012). Furthermore the 50th percentile of the positions of the four breakpoints relative to curve start and curve end were calculated, because the aim is to generate 85th percentile speed profiles using these positions. The distribution of the positions of breakpoints (boxplots in Figure 4-4) is rather similar along the different speed percentiles, as shown in Figure 4-4. So, using the 15th or 85th percentile positions, would result in skewed profiles, meaning the presented deceleration or acceleration would be too steep or to flat.

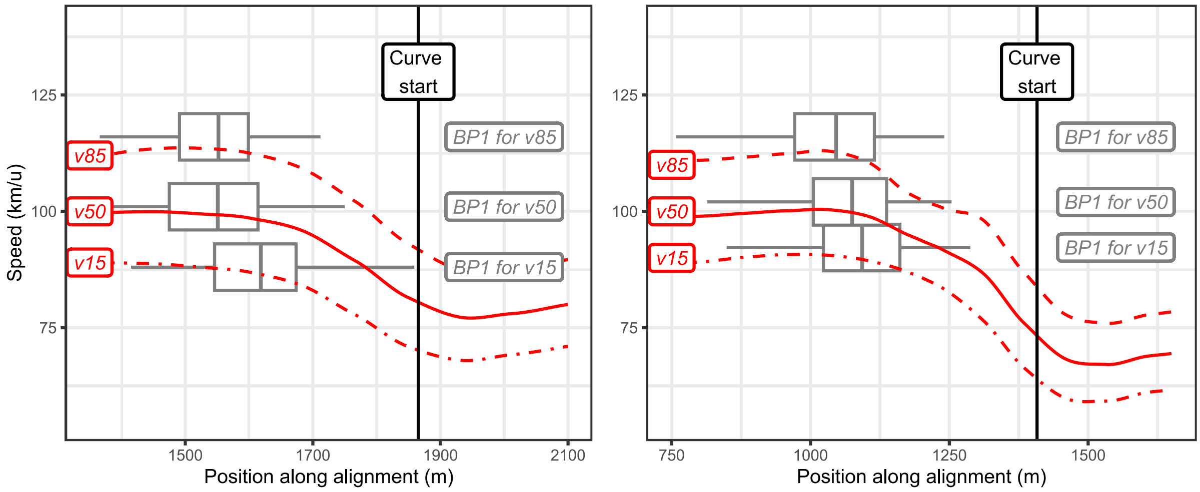


Figure 4-4 Two examples showing the 15th, 50th and 85th speed profile, and their respective distributions of positions of BP1 and the position of curve start along the alignment.

The values for the *v85* and positions of the breakpoints are plotted in Figure 4-5, shown in relation to the horizontal radius of the curve. The grey points represent all the 153 curves in the dataset, the black points represent the specific group used. The used groups show a lesser variability than the entire set, which is to be expected.

Figure 4-5A shows how drivers tend to start braking more ahead of a curve ($pos50_{BP1}$), when the radius decreases. This makes sense, because a greater amount of speed has to be reduced. Figure 4-5B shows a rather very mild increase in speed at BP1 ($v85_{BP1}$) with a mean of 124 km/h, which is to be expected, since no major influence of the curve is expected here because relative long tangents are positioned upstream of the first curves. The slight slope towards smaller radii can be explained by the fact that some small radii in The Netherlands are designed on separated carriageways in junctions, which tend to have lower speeds. Figure 4-5C, 4-5E, 4-5G and 4-5H show a firm correlation of speed throughout the curves, at curve start, BP2, BP3 and curve end ($v85_{CS}$, $v85_{BP2}$, $v85_{BP3}$ and $v85_{CE}$) to the horizontal radius, respectively. Figure 4-5D and 4-5F show a weak correlation of the position where drivers stop decelerating in a curve ($pos50_{BP2}$) and start accelerating out of a curve ($pos50_{BP3}$). These positions are however rather constant at around 75 m. after curve start for BP2 and 75 m. before curve end for BP3. Figure 4-5I shows it takes drivers longer to gain a constant speed after leaving curves ($v85_{BP4}$) with lower radii, which is explained by the greater speed increase. Lastly, Figure 4-5J shows that drivers adopt a lower speed after leaving a curve with a small radius at BP4 ($pos85_{BP4}$) than when they leave a curve with a relative large radius.

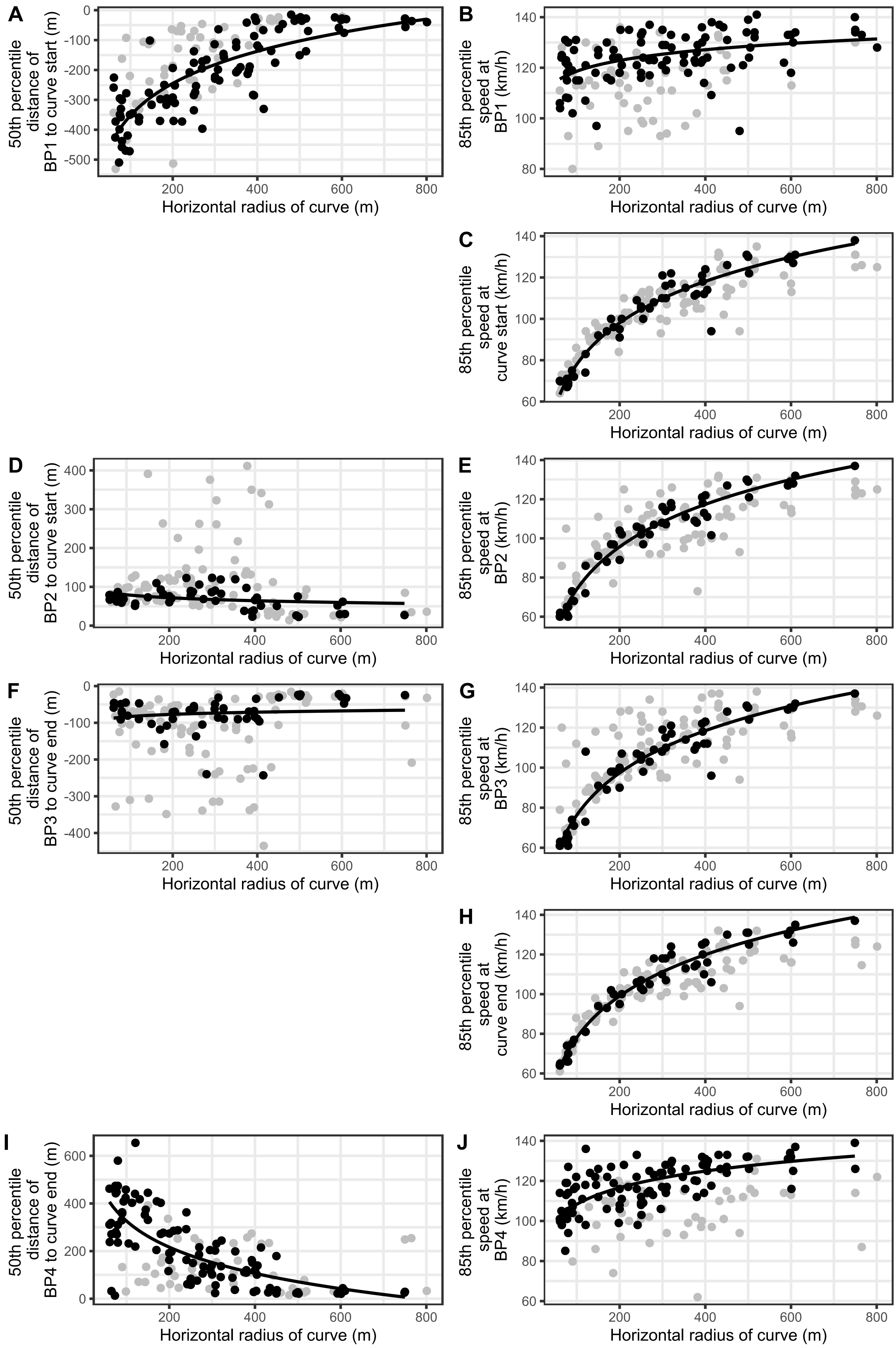


Figure 4-5 Scatterplots comparing horizontal radius to the 85th percentile of speed and median positions of breakpoints. All 153 curves are represented in grey points. The used subset in black points refer in A and B to first curves, C through H to single curves, and for I and J to last curves.

The regression lines shown in Figure 4-5 can be used to calculate coordinates of speed profiles based on horizontal radii. For example, using Figure 4-5A for the position of BP1 and Figure 4-5B for the 85th percentile of speed at BP1, it can be determined where drivers start to decelerate upstream of curve start and at which speed. In Figure 6 these coordinates were calculated for a set of horizontal radii to generate speed profiles based on breakpoints. Figure 4-6A shows the speed profiles for different horizontal radii upon curve entry, based on the following coordinates: ($pos50_{BP1}$, $v85_{BP1}$), (0, $v85_{CS}$), ($pos50_{BP2}$, $v85_{BP2}$). Figure 4-6B shows the speed profiles for different horizontal radii upon curve exit, based on the following coordinates: ($pos50_{BP3}$, $v85_{BP3}$), (0, $v85_{CE}$), ($pos50_{BP4}$, $v85_{BP4}$). Figure 4-6A shows deceleration slopes, which get steeper if the radius decreases below 300, meaning drivers brake harder in front of relative small radii. The opposite is true for acceleration out of a curve. Figure 4-6B shows that the acceleration is rather constant out of a curve, but decreases when radii increase over 300 m. Furthermore, Figure 4-6 shows that deceleration and acceleration is greater upstream and downstream of the curve respectively, than inside a curve.

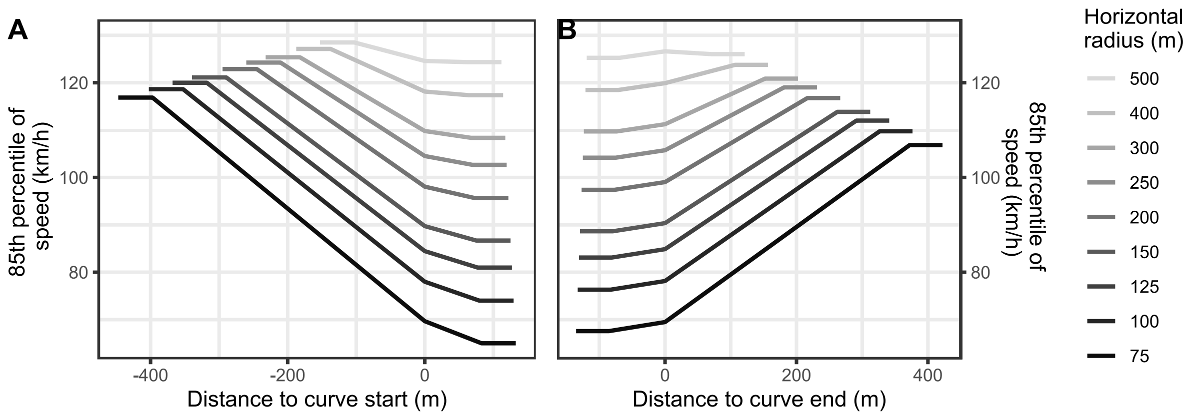


Figure 4-6 Profiles for the 85th percentile of speeds on different horizontal radii based on breakpoints and related to the start and end of the curve.

However, as seen in Figure 4-5, there is still some variability in the speed profiles as shown in Figure 4-6. A sensitivity analysis was done on which variables could explain this variability best. Using variables which are customary in design guidelines, and are easily distinguishable by drivers (Vos et al., 2021a), the influence of the number of lanes and the length of the curve were identified as extra factors explaining these variabilities. Figure 4-7A shows how the 85th percentile speed differs when having 1 lane in a curve compared to more lanes (notice that the regression lines for 2 and 3 lanes overlap). Figure 4-7B shows higher speeds in curve lengths shorter than 250 m. Appendix B contains the different subsets of these variables for the 85th percentile speeds, and for the positions of the breakpoints.

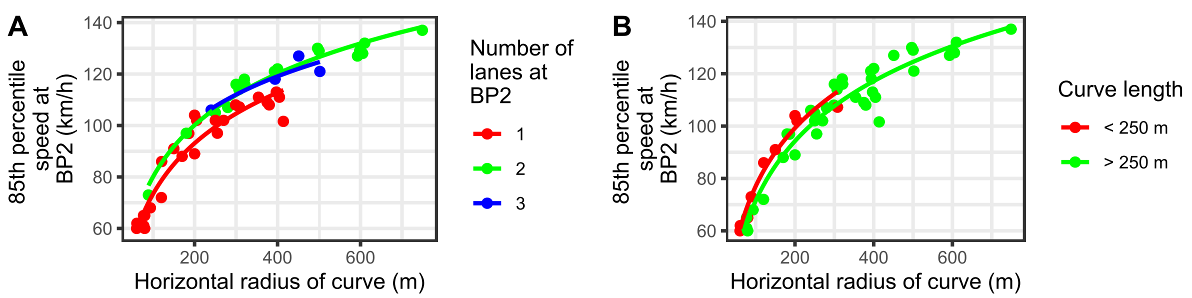


Figure 4-7 Sensitivity analysis on the number of lanes and length of a curve.

Adding the distinction between 1 lane or more to the model improved all the *v85* predictions significantly ($p < 0.001$). Collinearity between variables was checked, for example the distinction between 1 lane or more was not found to be correlated with $\ln(R_h)$ and was therefore used in the models. The correlation of $nLanes1_{BP1}$ with $\ln(R_h)$ is $r = 0.09$, for *nLanes1* is $r = 0.35$ and for $nLanes1_{BP4}$ is $r = -0.04$. For the positions of BP1 and BP4, adding extra variables did not result in better models. The models for the positions of BP2 and BP3 are very weak, and adding variables did not improve models significantly, so, to keep in line with BP1 and BP4 we chose not to add variables. Adding the curve length itself or the distinction of curve length being more or less than 250 meters only improved the *v85* predictions at BP2 and BP3. To create a continuous speed profile, the predictions from all speed and position models need to be combined. Adding curve length variables only in BP2 and BP3 models would mean that continuous speed profiles use different variables at different positions resulting in misalignments of speed prediction between CS and BP2, and BP3 and CE. So this variable was excluded for all breakpoints. This resulted in modelled speed profiles which align the observed data better, by using the below presented best subsets of variables to predict the coordinates of speed profiles. The coordinates are in the form of (*pos50*, *v85*) for each breakpoint.

$pos50_{BP1} = 155 * \ln(R_h) - 1067$ ($R^2 = 0.679$) [4-2]

$pos50_{BP2} = -11 * \ln(R_h) + 130$ ($R^2 = 0.078$) [4-3]

$pos50_{BP3} = 9 * \ln(R_h) - 122$ ($R^2 = 0.015$) [4-4]

$pos50_{BP4} = -159 * \ln(R_h) + 1057$ ($R^2 = 0.531$) [4-5]

$v85_{BP1} = 6 * \ln(R_h) + 4 * nLanes1_{BP1} + 88$ ($R^2 = 0.220$) [4-6]

$v85_{CS} = 26 * \ln(R_h) + 8 * nLanes1 - 41$ ($R^2 = 0.948$) [4-7]

$v85_{BP2} = 28 * \ln(R_h) + 7 * nLanes1 - 58$ ($R^2 = 0.961$) [4-8]

$v85_{BP3} = 27 * \ln(R_h) + 7 * nLanes1 - 51$ ($R^2 = 0.919$) [4-9]

$v85_{CE} = 27 * \ln(R_h) + 8 * nLanes1 - 47$ ($R^2 = 0.971$) [4-10]

$v85_{BP4} = 58 * \ln(R_h) + 4 * nLanes1_{BP4} + 58$ ($R^2 = 0.423$) [4-11]

where:

pos50 = 50th percentile of a position relative to curve start or curve end (distance in m.);

v85 = 85th percentile of speed (km/h);

R_h = horizontal radius of the curve (m.);

nLanes1 = distinction of having 1 or more lanes (0 = 1 lane, 1 = more lanes).

The R^2 of the different models show that the radius of the curve and the number of lanes explain well the variability in the speed inside a curve. The variability of the positions of BP1 and BP4 is moderately explained by the radius of the curve. The variability of speed at BP1 and BP4 is weakly explained by curve radius and number of lanes at these BPs, this is generally seen for speed prediction models on tangents (Hassan, Sarhan, Porter, et al., 2011). The mean speed at BP1 with more than 1 lane is 125 km/h (SD = 9.3 km/h). The radius of the curve does not explain well the variability observed in the positions of BP2 and BP3, but, as seen in Figure 4-5D and 4-5F, the positions of these points are rather constant and not influenced by the radius of the curve. $d50_{BP2}$ has a mean of 93 m. (SD = 72 m) and $d50_{BP3}$ has a mean of -106 m. (SD = 94 m.). Both have a median of 76 m. (negative for $d50_{BP3}$).

These models were compared on actual speed profiles to see how well they align with speed development in different situations. In Figure 4-8 actual observed 85th percentile speed profiles are shown in a red dashed lines. The different horizontal radii and positions of curve start (*CS*) and curve end (*CE*) were added, together with the number of lanes in relation to the speed profile. For each curve, a predicted speed profile based on the following coordinates (($pos50_{BP1}$ + *CS*), $v85_{BP1}$), (*CS*, $v85_{CS}$), (($pos50_{BP2}$ + *CS*), $v85_{BP2}$), (($pos50_{BP3}$ + *CE*), $v85_{BP3}$), (*CE*, $v85_{CE}$), (($pos50_{BP4}$ + *CE*), $v85_{BP4}$) was added. Figure 8A shows a single, relative sharp, curve. The predicted profile aligns well with both slopes, but we notice also deceleration upstream of BP1 and acceleration downstream of BP4, although being at a lesser slope. Figure 4-8B shows predictions of a set of curves with radii around 500 m. Only marginal speed development is seen and predicted. Figure 4-8C shows a set of curves with decreasing radii. The predictions follow the actual slope of entering the set of curves and exiting the set of curves. It also shows to negate the coordinates for BP3 to BP4 from the first curve and BP1 of the second, since they are smoothed together. Figure 4-8D shows this in a more extreme setting with two relative small radii curves, connected with a small tangent. Observed slopes of exiting the first curve and entering the second are quite well aligned with the predicted slopes. Figure 4-8E shows a set of three curves, of which the first two have about the same radius, and the last one is larger. The slope of entering the first curve of the set is quit smooth in the observed red line, but aligns about half way with the predicted line. Exiting the curve combination of curves was predicted at a steeper slope towards the third curve. Possibly drivers remain cautious towards the last curve. Finally, Figure 4-8F shows a complex road section with two sets of curves with each two curves and different numbers of lanes. In the tangent between the two sets of curves, a higher speed is predicted, but overall, the slopes are pretty well aligned with the observed speed. Overall, Figure 4-8 shows relative well alignment of predicted and observed speeds in the curves, as well as the slopes of acceleration and deceleration, but are less well aligned with speeds at tangents. It also shows that based on the predicted speeds, inconsistent designs can be revealed, because these designs do not show a smooth operating speed profile.

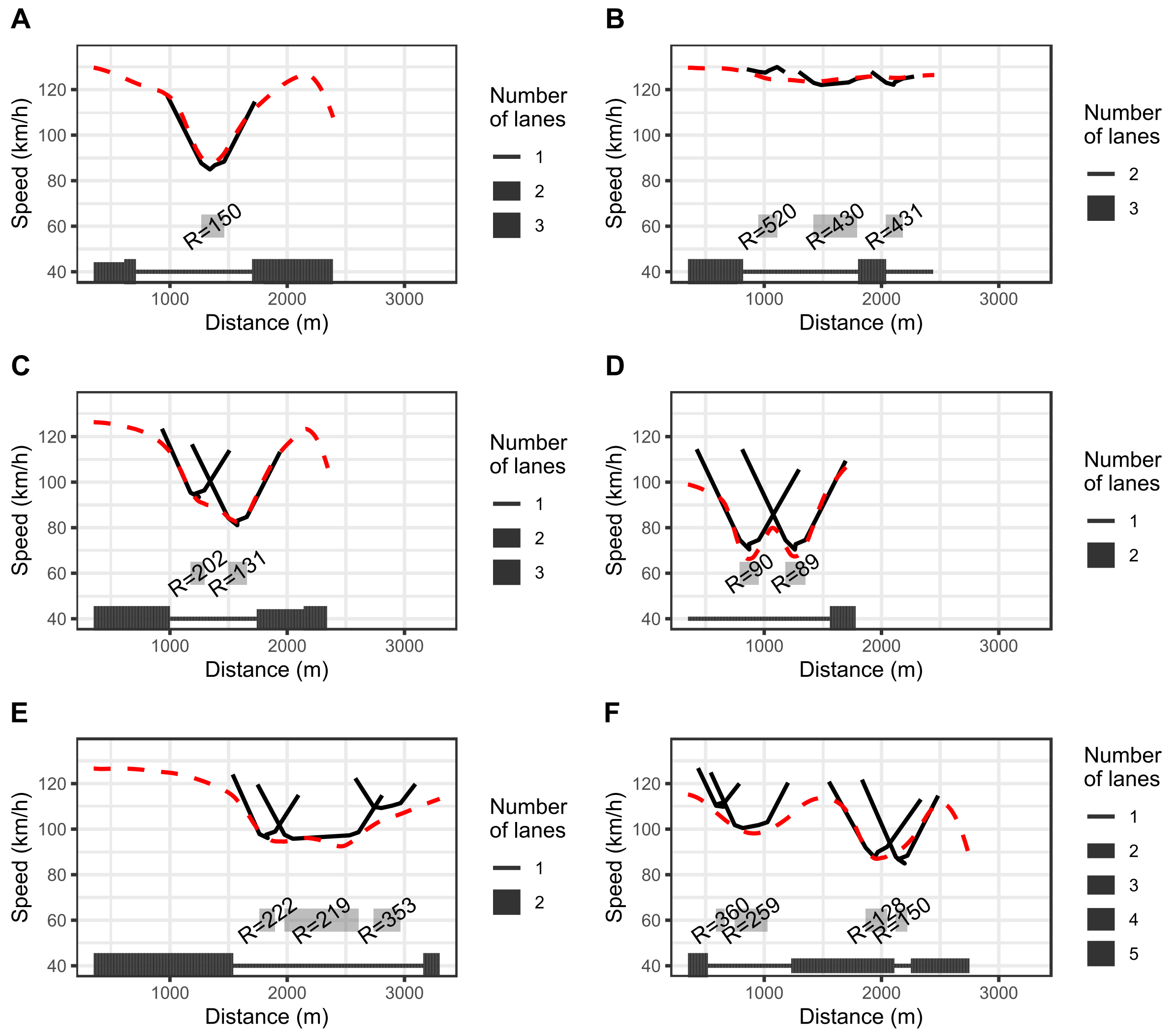


Figure 4-8 Observed and predicted speed profiles; red dashed line is the observed 85th percentile speed, the black lines are the predicted speed profiles per curve. Curve radii in a grey box representing the position of the curve. Below that a line indicating the number of lanes present along the profile.

In Figure 4-8, it was shown that the slopes that were predicted using the coordinates for the BPs and their respective 85th percentile speeds are rather accurate. So, based on these coordinates, the average acceleration and decelerations based on the different slopes can be calculated. Table 4-2 provides the outcomes of those calculations for the range of radii shown in Figure 4-6. As noticed in Figure 4-6, Table 4-2 shows rather constant decelerations and accelerations along the range of radii up to 250 meters. Larger radii seem to result in lower accelerations and decelerations. The exception is the deceleration from *CS* to BP1, which shows to increase with decreasing radii.

Table 4-2 Average decelerations and accelerations based on predicted slopes from 85th percentile speed profiles.

R_h (m.)	1 lane				2 or more lanes			
	Deceleration		Acceleration		Deceleration		Acceleration	
	BP1-CS (m/s^2)	CS-BP2 (m/s^2)	BP3-CE (m/s^2)	CE-BP4 (m/s^2)	BP1-CS (m/s^2)	CS-BP2 (m/s^2)	BP3-CE (m/s^2)	CE-BP4 (m/s^2)
75	-0.77	-0.29	0.12	0.61	-0.76	-0.40	0.18	0.57
100	-0.80	-0.29	0.13	0.64	-0.76	-0.39	0.19	0.58
125	-0.81	-0.27	0.13	0.65	-0.76	-0.38	0.20	0.58
150	-0.81	-0.25	0.13	0.66	-0.75	-0.37	0.20	0.57
200	-0.81	-0.20	0.13	0.66	-0.72	-0.33	0.21	0.53
250	-0.79	-0.16	0.13	0.66	-0.67	-0.29	0.22	0.48
300	-0.76	-0.11	0.13	0.63	-0.61	-0.25	0.22	0.41
400	-0.67	-0.02	0.13	0.54	-0.44	-0.16	0.22	0.19
500	-0.51	0.07	0.12	0.35	-0.18	-0.08	0.22	-0.22

4.3.2 Acceleration profiles based on the 85th percentile of deceleration and acceleration

In the previous paragraph the main focus was on analysing the slope in speed profiles to gain insights into deceleration and acceleration upon curve entry and curve exit. This paragraph enriches these insights, using the median positions where drivers maximize their decelerations and accelerations ($pos50_{MAXdec}$, $pos50_{MAXacc}$) and the observed 85th percentile of respectively the deceleration and acceleration ($a85_{MAXdec}$, $a85_{MAXacc}$) at those positions. This provides insights into the development of accelerations. Since the average acceleration inside of curves was found to be different from the average acceleration upstream and downstream a curve, the 85th percentile of deceleration and acceleration observed at respectively curve start and curve end ($a85_{CS}$, $a85_{CE}$) were also extracted from the data.

Figure 4-9 shows scatterplots of these variables in relation to the horizontal radius. Figure 4-9A shows that drivers tend to maximise their deceleration closer to the curve start when the radius is larger, and Figure 4-9B shows that drivers decelerate harder at that point and when the radius is smaller, which is the same for the deceleration at curve start, but in a lesser amount, as shown in Figure 4-9C. Figure 4-9D shows that at curve end acceleration out of a curve is faster when the radius is smaller. Acceleration is highest at a position after curve end, and gets closer to curve end as the radius gets larger, as shown in Figure 4-9E. Finally, Figure 4-9F shows that at that point of maximum acceleration, the acceleration is larger when the radius decreases.

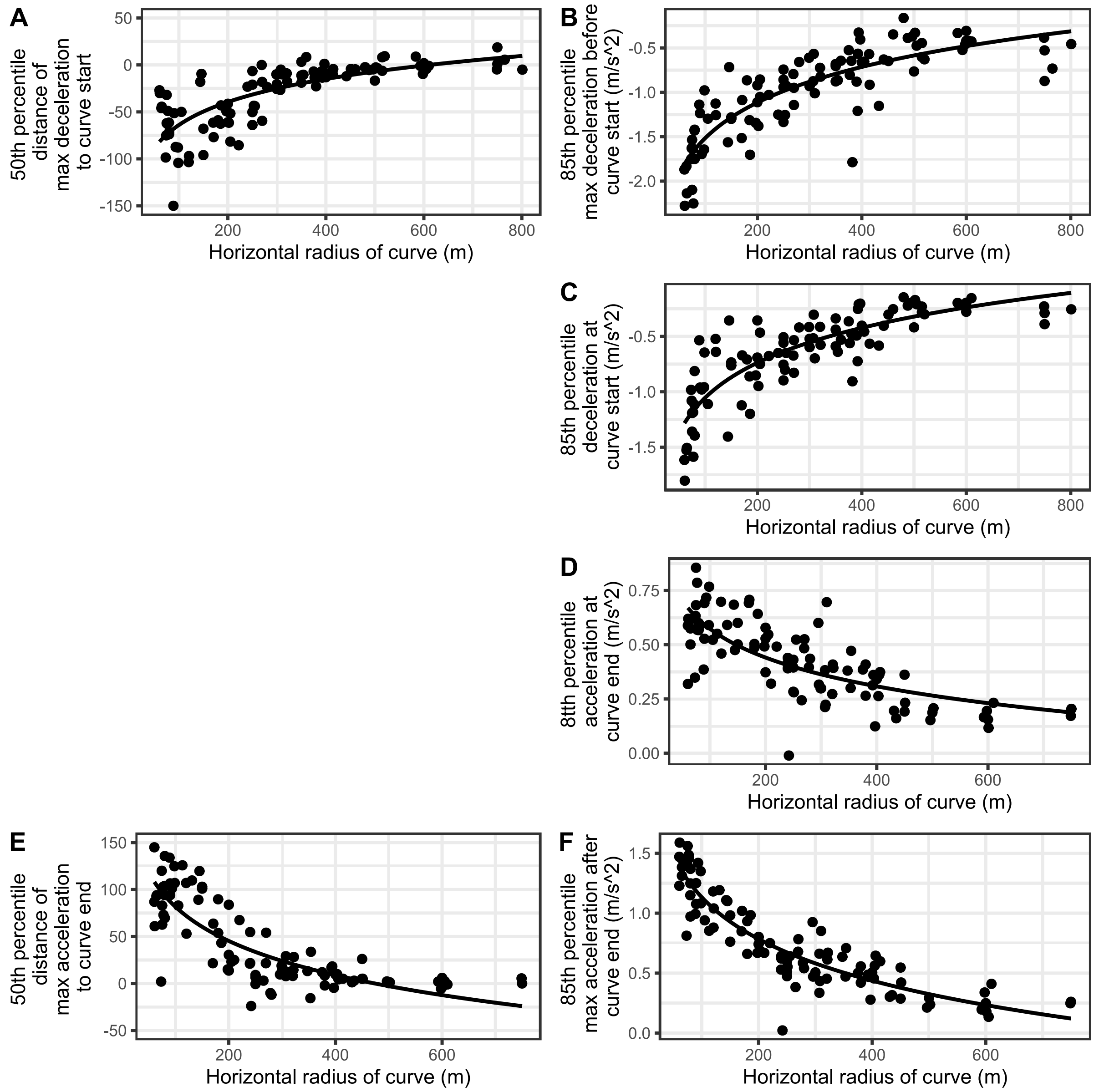


Figure 4-9 Scatterplots comparing horizontal radius to the 85th percentile of acceleration and deceleration as well as the positions of maximum acceleration and deceleration.

Breakpoints are defined based on the acceleration being 0 m/s² at those positions (Figure 4-3), so *pos50* (50th percentile of those positions) for each breakpoint can be used as a position in an acceleration profile where 0 m/s² is observed. By adding information from the regression lines in Figure 4-8, a deceleration and acceleration profile can be plotted based on the positions of the breakpoints, maximum acceleration, curve start and curve end. Figure 4-10 shows these acceleration profiles for the same set of horizontal radii used in Figure 4-6. Figure 4-10A shows the deceleration profiles upon curve entry based on the following coordinates: ($pos50_{BP1}$, 0), ($pos50_{MAXdec}$, $a85_{MAXdec}$), (0, $a85_{CS}$), ($pos50_{BP2}$, 0). Figure 4-10B shows the acceleration profiles upon curve exit based on the following coordinates: ($pos50_{BP3}$, 0), ($pos50_{MAXacc}$, $a85_{MAXacc}$), (0, $a85_{CE}$), ($pos50_{BP4}$, 0). Overall, Figure 4-10 shows the deceleration and acceleration development upstream and downstream of a curve.

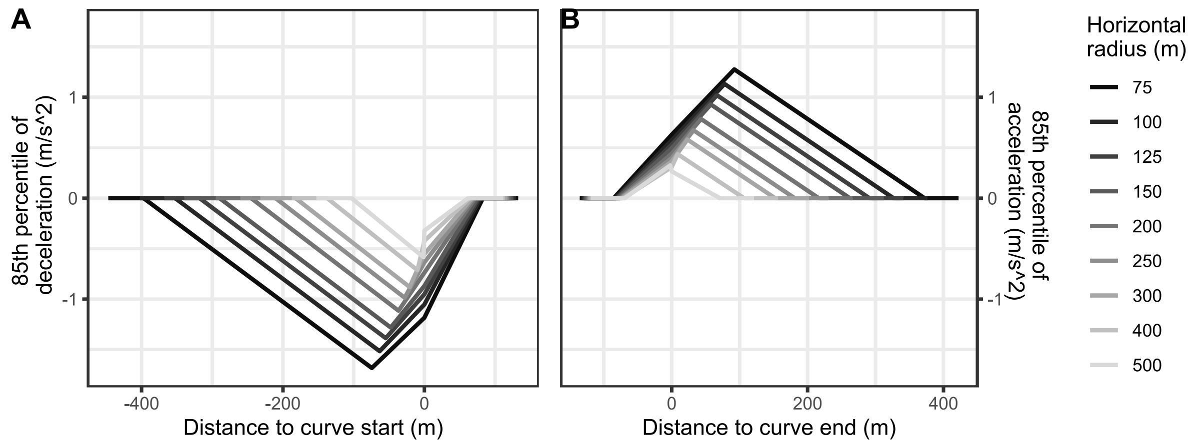


Figure 4-10 Profiles for the 85th percentile of deceleration and acceleration on different horizontal radii based on breakpoints and maximum acceleration.

Because Figure 4-9 shows variability around the regression lines, it was explored which variables might explain this variability. However, none of the variables added to the models contributed significantly to explaining this variability for the acceleration models. Appendix C shows the tested models. To keep in line with the other models for the 50th percentile of positions, no other variables were added to the positions of maximum deceleration and acceleration. The best subsets of variables for the additional coordinates needed for acceleration and deceleration profiles are given below:

$pos50_{MAXdec} = 39 * \ln(R_h) - 241$ ($R^2 = 0.351$) [4-12]

$pos50_{MAXacc} = -49 * \ln(R_h) + 307$ ($R^2 = 0.518$) [4-13]

$a85_{MAXdec} = -0.58 * \ln(R_h) - 4.18$ ($R^2 = 0.712$) [4-14]

$a85_{CS} = -0.46 * \ln(R_h) - 3.15$ ($R^2 = 0.702$) [4-15]

$a85_{CE} = -0.19 * \ln(R_h) + 1.46$ ($R^2 = 0.702$) [4-16]

$a85_{MAXacc} = -0.50 * \ln(R_h) + 3.44$ ($R^2 = 0.825$) [4-17]

where:

pos50 = 50th percentile of a position relative to curve start or curve end (distance in m.);

a85 = 85th percentile of acceleration (m/s²);

R_h = horizontal radius of the curve (m.).

The R^2 values reveal relatively strong goodness-of-fit of the predicted 85th percentiles of deceleration and acceleration, while the goodness-of-fit of the models predicting positions of maximum deceleration and acceleration are relatively weak.

These models were compared on actual acceleration and deceleration profiles, taken from the same road sections as Figure 4-8. In Figure 4-11 the 15th percentile and 85th percentile of acceleration were plotted in green dashed lines. The 15th percentile of acceleration is used as the 85th percentile of deceleration. The start and end of each curve was also included. Based on these positions of the curves, the predicted acceleration profiles per curve were created based on the following coordinates: (($pos50_{BP1}$ + CS), 0), (($pos50_{MAXdec}$ + CS), $a85_{MAXdec}$), (CS, $a85_{CS}$), (($pos50_{BP2}$ + CS), 0), (($pos50_{BP3}$ + CE), 0), (CE, $a85_{CE}$), (($pos50_{MAXdacc}$ + CE), $a85_{MAXacc}$), (($pos50_{BP4}$ + CE), 0). Figure 4-11A shows a relative good match to the deceleration and acceleration around a single curve. Figure 4-11B shows that the predicted acceleration and decelerations of curves with radii around 500 meter are not detectable by the 15th and 85th percentiles of observed acceleration. Figure 4-11C shows that with a set of curves, only the deceleration up to the first curve, and the acceleration after the last curve are aligned well. Between the two curves, the acceleration remains rather neutral, because speed was already adjusted in the first curve. Figure 4-11D shows that if the curves are a bit more apart, parts of the acceleration and deceleration between the curves are aligned, but with an offset. Figure 4-11E shows how the model aligns the acceleration upstream of the third curve relatively well, based on de acceleration out of the second curve. Figure 4-11F finally, shows how the deceleration before the second set of curves is aligned relatively well, based on the tangent between both sets of curves. In general, Figure 4-11 shows acceleration profiles are relatively well aligned for curves surrounded by tangents. For sets of curves, only the deceleration into the first curve, and acceleration out of the last curve are relatively well aligned. The acceleration profile between consecutive curves should be examined based on the speed profile mostly; if the speed remains relatively the same, no acceleration is observed.

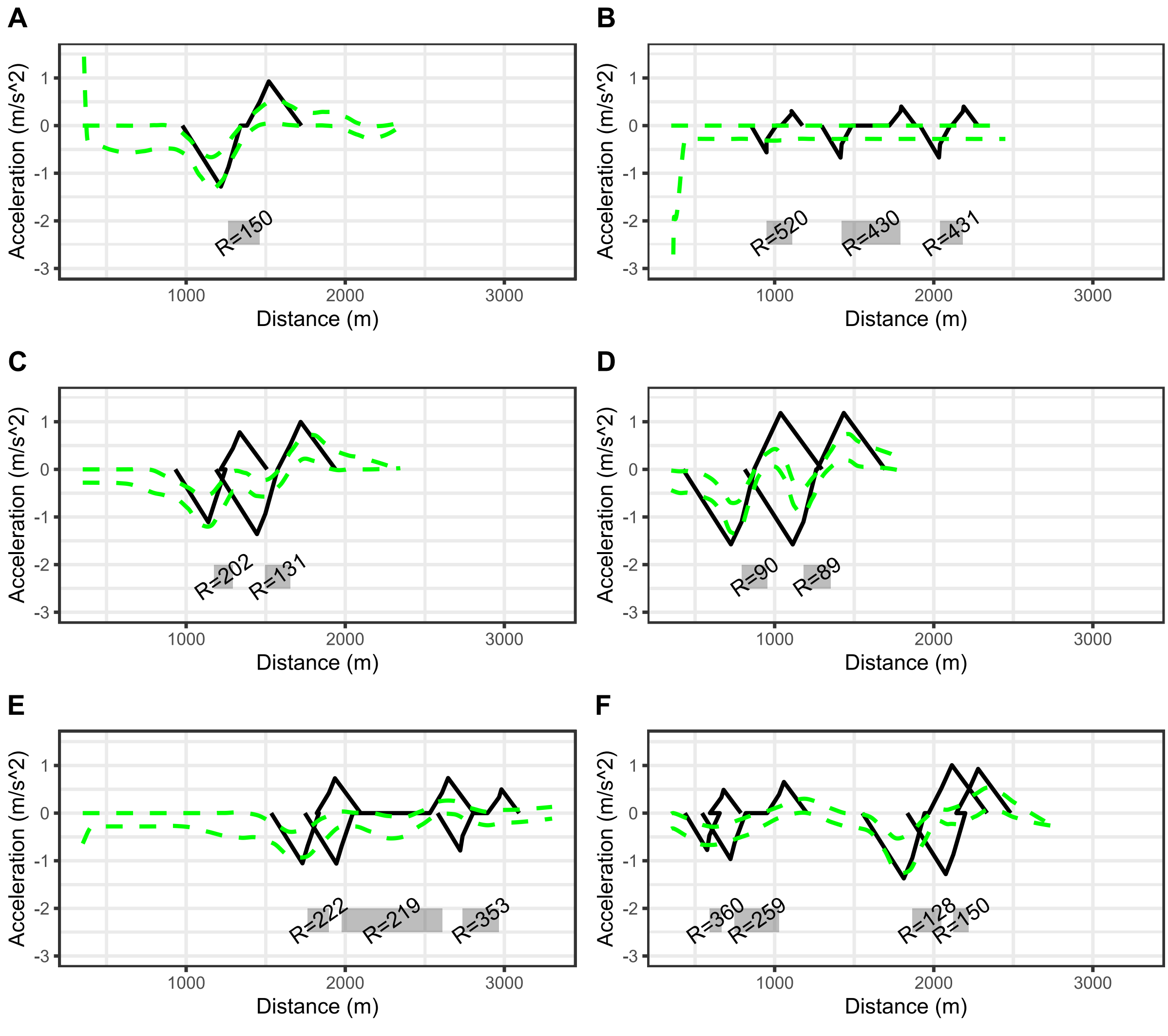


Figure 4-11 Observed and predicted acceleration profiles; green dashed lines are the observed accelerations at 15th and 85th percentile, the black lines are the predicted acceleration profiles per curve. Curve radii in a grey box representing the position of the curve. These acceleration profiles are taken from the same curves as presented in Figure 4-8.

4.4 Discussion and limitations

The strong correlation between the horizontal radius to speed and acceleration is confirmed, which is also shown in numerous other studies (Farah et al., 2019; Hassan, Sarhan, Porter, et al., 2011). When identifying the slopes in the speed profiles when entering a curve, the results show different findings from those by Alfonso Montella et al. (2015) where increasing slopes were found when the radius decreases. This study found a relation only between the radius of the curve and the 85th percentile of maximum decelerations, not to the average decelerations.

Also in line with other studies, this study was unable to present strong correlations between the speed on tangents and the geometric elements. The speed on tangents upstream of a curve are of importance to predict the deceleration before the curve. The predicted slopes in speed profiles are generally well aligned with the observed slopes, which are the average deceleration calculated based on speeds on tangents and in the curve.

The acceleration models show a lesser goodness of fit than the speed models. This could be explained because acceleration is treated as a derivative of speed in this research. The slopes of the acceleration models were not further investigated, because of increasing uncertainties in the derivations. The slope of acceleration is known as the longitudinal jerk (m/s^3) and has limited influence on general traffic safety, but can be used to identify individual aggressive drivers (Feng et al., 2017).

It was the aim of this study to include only variables which are easily extracted from a geometric design, namely horizontal radius, start and end position of curves, and the number of lanes. Other, more complex variables (Vos et al., 2021b), might improve the models further, but are harder to implement in design evaluations. Furthermore, variables such as type of roadway, superelevation, transition curves, Curvature Change Rate or weather conditions do not have significant impact on speed behaviour or are collinear to horizontal radius (Vos et al., 2021b).

The length of a curve was omitted from the regression models, as it was shown in the analysis to be insignificant for predicting the speeds at breakpoint outside of the curve. The models however show acceleration and deceleration inside a curve. So, with shorter curve-lengths acceleration and deceleration will overlap and visually show unrealistic speed development. This predicts a higher speed inside a curve then predicted by $v85_{BP2}$ and $v85_{BP3}$. More research is needed to understand the smoothing of the profiles, based on the current insights of the breakpoints.

The 85th percentile of observed speeds before drivers start to decelerate upstream of a curve confirm the selected design speed of 120 km/h for main carriageways with two or more lanes. Based on the 85th percentile of speeds observed inside the curves, we noticed discrepancies up to 30 km/h towards the design speeds used for designing freeway curves in The Netherlands (Rijkswaterstaat, 2022). These insights can be used to evaluate safety risks which arise from these discrepancies, such as friction demand, sight distances both horizontally and vertically, forgiving shoulder design, etcetera.

The regression models shown in this study are based on radii ranging from 60 to 800 meters. It was noticed that when radii larger than 500 meters are used in these models, unrealistically high values are predicted. It seems the 85th percentile speed and acceleration are only influenced by radii smaller than 500 meters.

Since the sample of drivers in this study showed to drive on average 5.4 km/h faster over the loop detectors, it is assumed that the 85th percentile speeds shown and predicted in this study, are lower for the entire population.

4.5 Conclusions

Insights were gained in this study on speed and acceleration development upstream and downstream of freeway curves based on a highly detailed data-set containing High Frequency Floating Car Data combined with re-engineered road sections and detector loop data. Slopes in predicted speed models, as well as predicted maximum deceleration and acceleration, based on the horizontal radius and number of available lanes align well with the observed speed and acceleration data. Furthermore, distinction between acceleration outside and inside a curve was made, which is of importance to design evaluation related to friction. We show that inside a curve besides lateral friction, also longitudinal friction is absorbed. This deviates from design guidelines in which only lateral friction is used to calculate curve radii. Differences in deceleration and acceleration patterns outside and inside the curve are observed, with decreasing curve radii, drivers decelerate stronger in a curve.

Speed and acceleration development are predicted based on the coordinates of breakpoints. Breakpoints identify positions relative to curve start and curve end where drivers start and stop accelerating. Combining these positions with the 85^{th} percentile of speed, speed development can be predicted. It is shown that the speed development in a curve can be strongly explained by the horizontal radius and whether the curve has one or more lanes. The correlations to the speed development on the tangents were weaker, but the predicted slopes in the speed profiles (which represent deceleration or acceleration) align well with the observed speed development. Furthermore, the speed development around consecutive curves is reasonably well predictable, using the developed predictive models per curve, gaining insights into speed development by their overlapping characteristics. Acceleration development was further investigated by gaining insight into the positions where maximum deceleration and acceleration is reached and the 85^{th} percentile of those observations. The observed acceleration profiles for entering a first curve and exiting a last curve also align reasonably well to the predicted acceleration development. Acceleration inside a set of curves is not predictable based on our models, because our models assume acceleration outside of a curve, while a follow-up curve might not induce this.

The presented models are ready to be implemented into geometric design evaluation, because they show how speed and acceleration develops based on the position of the curve. Furthermore, the models can give insights into the needed acceleration and deceleration lengths around relative sharp curves in freeway connector roads. Because the speed development can be predicted, designers can check the needed sight distances, signage or even the needed friction, as well as speed inconsistencies.

The presented speed observations confirm the design speed on main carriageways based on the 85^{th} percentile of observed speed. The design speeds in curves however do not match up with the observed 85^{th} percentile of speed in this study confirming similar findings of previous studies.

5 On-Road Study to Uncover Which Cues Drivers Use in Curve Approach

This chapter has previously been published as: ***Vos, J.***, *de Winter, J., Farah, H., & Hagenzieker, M. (2023). Which visual cues do drivers use to anticipate and slow down in freeway curve approach? An eye-tracking, think-aloud on-road study. Transportation Research Part F: Traffic Psychology and Behaviour, 94, 190-211.*

Abstract

Although much research is done on speed and gaze behaviour inside curves, there is little understanding of which cues drivers use to anticipate and slow down while approaching curves. Therefore, an on road experiment was conducted in which 31 participants drove through six freeway curves in their own car. During the experiment, look-ahead fixations and speed were recorded using an eye-tracker and a GPS tracker, respectively. In addition to these measurements, the participants verbalised their reasons for changing speed. The distribution of fixations over various areas of interest was investigated around the start of deceleration before each curve and around the start of each curve. Verbalisation data were analysed to infer the number and types of reasons for changing speed and when these were mentioned together with mentions of deceleration before a curve. The results showed that before starting to decelerate, the participants fixated mostly on the Focus of Expansion and edges parallel to the curve trajectory, whereas most fixations on warning or speed signs were recorded mostly after participants started to decelerate. These findings suggest that drivers use information from the Focus of Expansion, be it a change in optical flow or the presence of a kink in the alignment, as the main cue to start decelerating. Parallel edges are also important cues, whereas warning and speed signs are primarily used to confirm that a speed change is needed.

5.1 Introduction

Freeways are designed to maintain a high speed throughout the trip, in accordance with drivers’ expectations regarding operating speeds on freeways. At the same time, it is imperative that drivers anticipate any curves well in advance and reduce their speed to navigate the curvy parts of the freeway safely. There is a lot of research on curve driving itself, both into speed behaviour (Malaghan et al., 2020; Vos & Farah, 2022) and perception (Lehtonen et al., 2018; Macuga, 2019), but driving task analysis (Campbell et al., 2012) shows that the anticipation of a curve starts far ahead of a curve and has considerable perceptual and cognitive requirements, i.e. where drivers look and how they judge this visual information. Freeways are considered to be self-explanatory (Theeuwes, 2021; Walker et al., 2013), meaning that the driver knows when speed reduction is required based on a uniform road design. But there is limited research investigating which cues from the road design and environment drivers use to reduce their speed before a curve (Vos et al., 2021a). This research aims to gain insight into which visual information is used by the driver in curve approach and how this is related to deceleration before a curve.

Deceleration in curve approach has been modelled based on speed differences before and in the curve (Altamira et al., 2014; Hassan, Sarhan, Porter, et al., 2011; Malaghan et al., 2021), but these models primarily use geometric elements as independent variables; attentional measures such as speed signs and warning signs are usually ignored. Moreover, deceleration models only reveal the amount of deceleration before a curve and not the position where deceleration starts (Vos & Farah, 2022), that is, the position where a driver starts to act towards the curve. Besides that the horizontal radius of the curve correlates to the position where a driver starts to slow down, Vos et al. (2021b) showed that sight distances also correlate to this position, indicating the relevance of visual information the driver uses. Lehtonen, Lappi, Kotkanen, and Summala (2013) showed that during perceptual exploration of the road, a distinction could be made between guiding fixations and look-ahead fixations, which correspond, respectively, to the near and far points in the two-point steering model (Neumann & Deml, 2011; Salvucci, 2006). Guiding fixations are task-relevant fixations that precede action by about 1–2 s of driving (Mole, Pekkanen, Sheppard, Markkula, & Wilkie, 2021), whereas look-ahead fixations are fixations on objects relevant to future actions (Lehtonen et al., 2013; Mennie, Hayhoe, & Sullivan, 2007; Sullivan, Ludwig, Damen, Mayol-Cuevas, & Gilchrist, 2021). While driving on a tangent, the near point tends to be in the centre of the lane or on the car in front (Salvucci & Gray, 2004), and the far point is positioned on the horizon, where the lines in the environment seem to be still while the driver moves forward, that is, the point from which all optical flow vectors expand, also known as the Focus of Expansion after Gibson (1950). The guiding fixations in curve driving are usually aimed near the tangent point of the curve or the car ahead (Land & Lee, 1994; Lappi & Lehtonen, 2012; Shinar et al., 1977), and the look-ahead fixations are aimed more downstream in the curve towards what is identified as future point, far point (Lappi, 2014), or occlusion point (Lehtonen et al., 2013). The curve radius itself – which is highly correlated to the operating speed – is hard to perceive by drivers because it appears as a hyperbola on the retina due to its viewing angle (Brummelaar, 1975; Fildes & Triggs, 1985; Springer & Huizenga, 1975). Therefore, curve warning signs, special markings, and delineation are used to help the driver anticipate the curve correctly and choose a safe speed in the curve (Bella, 2013; Charlton, 2007; Costa, Figueira, & Larocca, 2022). This is in line with task descriptions of curve approach, which mention signs and visible road direction changes as indicators for curve anticipation (Campbell et al., 2012; McKnight & Adams, 1970). Drivers themselves indicate that a good view of the trajectory and the presence of guiding elements are important for choosing a suitable speed (Vos et al., 2021a). It is however difficult for drivers to reflect on speed choices. That is because speed reduction during curve approach is an operational driving task (Michon, 1985) and is a skill-based process (Ranney, 1994) and therefore does not involve active thinking while driving. Speed reduction during curve approach can hence be described as subconscious. Charlton and Starkey (2011) showed that during unaware driving, correct motor responses are still produced. Similarly, in unaware locomotion, perceptual and cognitive processing is still present (Harms, van Dijken, Brookhuis, & de Waard, 2019). This research aims to gain insights in these perceptual and cognitive processes and identify the visual cues drivers use before and during deceleration while approaching a curve. To achieve this, two main research questions were formulated:

- Where do drivers look during curve approach, and how does this relate to deceleration?
- What do drivers report as important cues related to speed reduction during curve approach?

To investigate these research questions, an on-road study was conducted. A field study was chosen because a laboratory setting might disturb the unawareness of the driving behaviour (Shinar, 2017a). Furthermore, road geometry in laboratory settings (e.g., driving simulators) might not be representative of the real world (Bobermin et al., 2021). Familiarity with the test route may however bias the looking behaviour and driving speeds of local participants (Pratt et al., 2019; Young, Mackenzie, Davies, & Crundall, 2018), so this was also tested. We used portable eye-tracking, concurrent think-aloud procedures, and GPS tracking — a combination that has been proven valuable in investigating information processing thanks to the complementarity of the methods (Kircher & Ahlstrom, 2018; Lenne, Salmon, & Young, 2011). Eye-tracking has been used in driving experiments for several decades and has contributed to our understanding of which visual information is used during driving processes (Crundall & Underwood, 2011). We focus on look-ahead fixations, since these are thought to reveal which cues are used to anticipate a curve. Concurrent think-aloud techniques can reveal in real-time what visual information drivers use to start an action (Read, Beanland, Lenné, Stanton, & Salmon, 2017), such as deceleration.

The following section, section 2, describes the methods of the experiment. The results are reported in section 3 and discussed in section 4. Finally, the main conclusions of this research are presented in section 5.

5.2 Methods

5.2.1 Participants

Thirty-one participants (5 female, 26 male) were recruited through the professional network of the first author and via the ANWB – the Royal Dutch Touring Club. None of the participants wore glasses. Participants had to own and bring a passenger car and their driver's license. The research was approved by the Human Research Ethics Committee of the Delft University of Technology (letter of approval 1717). The participants had a mean age of 41.5 years (*SD* = 13.3 years) and a mean driving experience of 21.8 years (*SD* = 13.2 years). Most participants indicated being frequent drivers; only three indicated driving less than one day a week, while seven indicated driving every day. Participants were offered a €50 gift certificate for their time and car fuel.

5.2.2 Procedure

In order to capture how the participants interact with the road layout rather than other surrounding traffic, the experiment was carried out outside of peak hours in daylight settings, from 9:30 to 15:15.

Before the experiment, the participants were asked to sign an informed consent form and to fill in a NASA-TLX standardised test (Hart, 2006) regarding their drive to the location of the experiment. Next, the eye-tracker was calibrated, and the participant was asked to, during the experiment, reflect on their speed adaptations: *"I want you to explain to me why you change your speed during the drive on the freeway. Try to constantly answer the question "how can you tell you need to slow down or speed up?". In other words, please explain how you choose your speed. Please speak in your own words and drive like you normally would"*. By keeping the aim of verbalisation towards speed change in general, the participants were not biased towards curves. The participants then drove the route shown in Figure 5-1, which lasted 33 minutes on average. During the drive, the participants wore the eye-tracker, and a portable GPS tracker was placed in the participants' car to record speed and position. The participants were asked to switch off their ADAS, as we were interested in speed reduction by the human driver and not by any autonomous system. The experimenter sat in the back seat of the car, giving route directions to the participant by orally mentioning the target direction (e.g. Amsterdam) on the upcoming route signage, keeping an eye on the recordings, and nudging the participant when deviating from the think-aloud protocol. After the experiment, the participants completed another NASA-TLX regarding their drive during the experiment. Furthermore, the participants were asked to rate their familiarity with each curve on a Likert-scale from 1 (not at all familiar) to 10 (very familiar) (Harms, Burdett, & Charlton, 2021) using a map, pictures of the road or help from the experimenter to identify the curves, and to reflect on the experiment in terms of how they experienced it and how they anticipated curves in a post-experiment questionnaire. During the experiment, all communication, including the think-aloud, was done in Dutch.

5.2.3 Test route

The test route was located on the freeways to the south of Amsterdam, had a length of 39 km, and included six curves of interest, see Figure 5-1. The alignment of the curves was reconstructed in Civil3D using road measurements from the road authority to provide information about relevant geometric elements, such as the horizontal radii and the start of the continuous curve. The alignment starts at the position where the first route signage for the given direction is present and ends at the end of the connector road. The constructed alignment sections act as the scope of the data processing; data outside these sections was not processed.

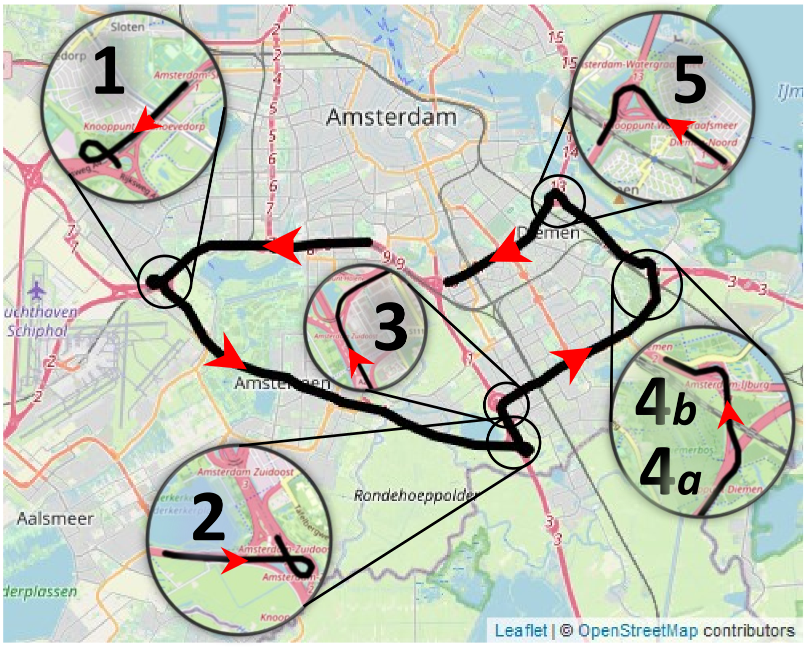


Figure 5-1 The route participants drove and the selected six curves analysed in this study.

Curve 1 is positioned after a two-lane deceleration lane. The curve itself remains obscured by a noise barrier that ends approximately 150 m upstream of the curve. The curve has a horizontal radius of 105 m. Just after the noise barrier, an advisory speed sign showing 50 km/h is positioned on the right shoulder. Curve 2 is the end of a main carriageway consisting of two lanes. It has a horizontal radius of 88 m. The curve is preceded by speed limit signs showing 80 km/h and 60 km/h and flashing warning signs at 700 m, 400 m, and 250 m upstream of the curve on both shoulders. Curve 3 is a direct connector road with a horizontal radius of 250 m. A two-lane weaving section precedes this curve, and at the start of the curve, an advisory speed sign indicating 80 km/h is positioned on both shoulders. Curve 4a is preceded by a single lane split and a speed limit sign of 80 km/h positioned on the right shoulder of the curve. The curve has a horizontal radius of 360 m. The connector road continues with a curve and a tangent of approximately 1600 m consisting of two lanes. This is followed by Curve 4b with a horizontal radius of 128 m. The curve is mostly obscured by an overpass and preceded by advisory speed signs showing 50 km/h on both shoulders. Curve 5 is the shortest, with a length of 150 m and a horizontal radius of 300 m, and is preceded by a three-lane asymmetrical weaving section. The curve is not preceded by warning signs. Following Curve 5, signs are in place for the remainder of the connector road. Curves 4a, 4b, and 5 are followed by other curves, which are not analysed because the speed behaviour in these curves would be influenced by the preceding curves (Kim & Choi, 2013; Vos, 2022). Figure 5-2 shows dashcam pictures at the approximate median positions where deceleration starts.

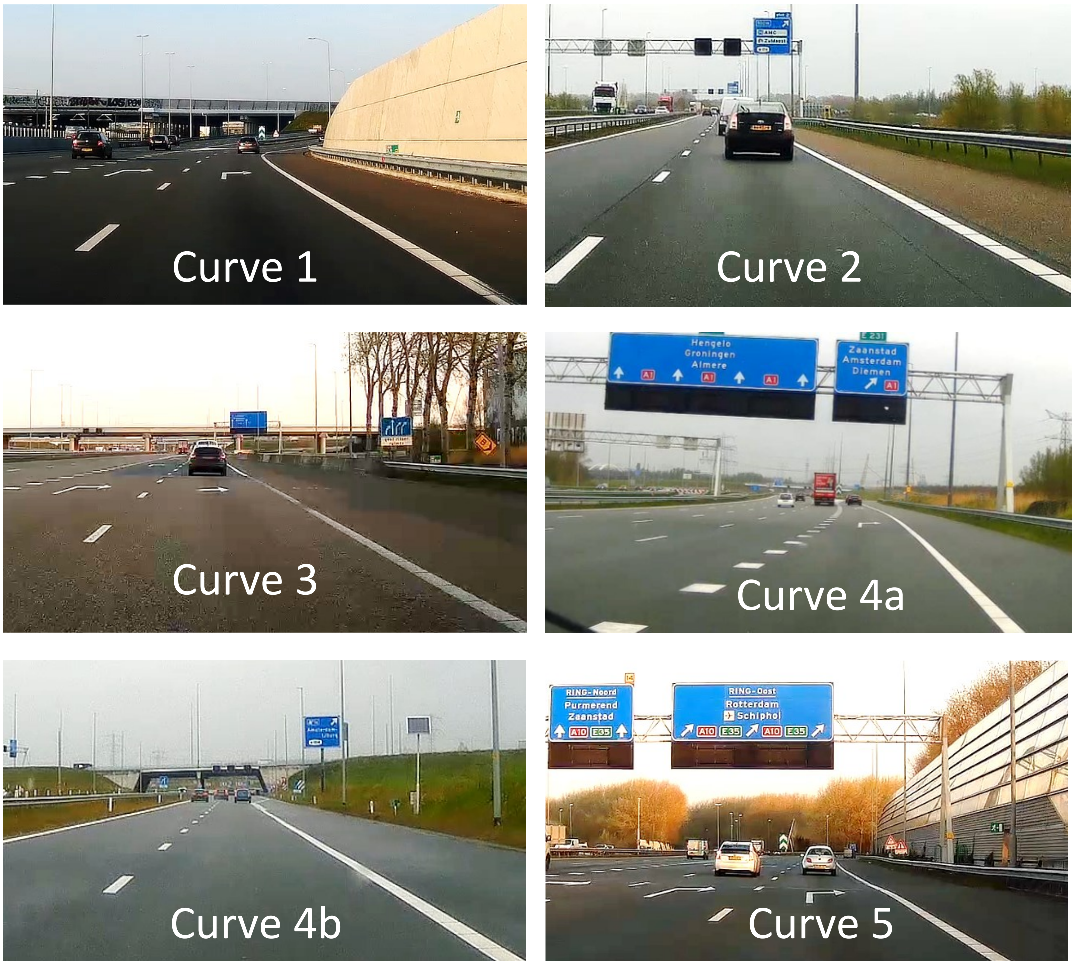


Figure 5-2 Dashcam pictures at the approximate median positions where deceleration before each curve starts. Google maps locations via these hyperlinks: Curve 1, Curve 2, Curve 3, Curve 4a, Curve 4b, Curve 5.

5.2.4 Data collection

The Qstarz BT-Q1000XT GPS-logger recorded the position and speed of the participants' car at a rate of 1 Hz and with a known accuracy of 78.7% of the recorded location within 10 m of the expected location (Schipperijn et al., 2014). The Tobii Pro Glasses 3 records the participants' gaze data at 60 Hz and an HD video in the looking direction of the participant. The participants' verbalisations were also recorded by the Tobii Pro Glasses 3 in the HD video.

5.2.5 Data analysis

5.2.5.1 GPS data

First, the GPS data points per participant were individually related to the closest position on the reconstructed alignment of the curves to have timestamps connected to specific positions along the alignment. Next, the acceleration profile was derived from the speed data by dividing the speed change in km/h every second by 3.6 to get acceleration in m/s^2. Based on this acceleration profile, we were able to identify the last position upstream of the start of the curve where the participant maintained 0 m/s^2. This position is illustrated in Figure 5-3 and served as the position where the driver initiated action while approaching the curve, that is, the start of deceleration before the curve (Vos et al., 2021b). Furthermore, based on the eye-tracking video, it was determined whether a participant was driving free-flow, i.e., having a minimum headway of 5 seconds (Hashim, 2011).

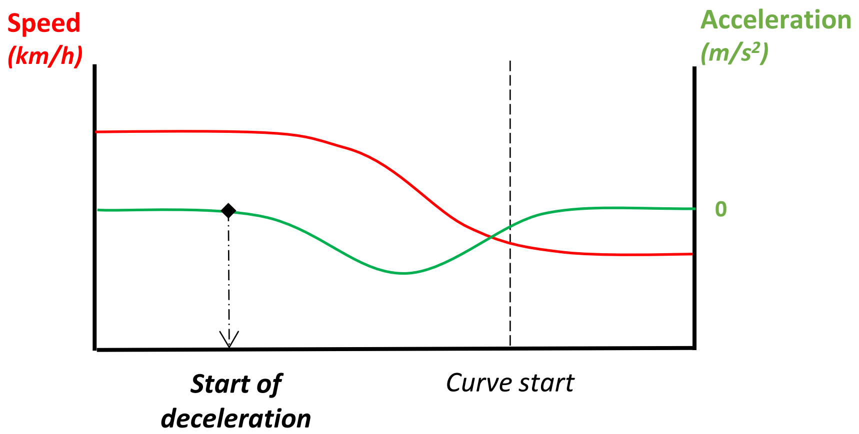


Figure 5-3 Theoretical speed and acceleration profile showing the starting point of deceleration relative to the start of the curve.

5.2.5.2 Fixation data

The analysis of the gaze data was done in the Tobii Pro Lab (Tobii Pro, 2021), which enables manual labelling of Areas of Interest. The software shows the percentage of gaze samples per participant. When this was below 80%, it was analysed which individual curves had a coverage over 80% and could therefore be included in the analysis. The raw data were compared with the pre-set filters in the software, and it was concluded that the "attention filter" showed the most meaningful results in our dynamic experimental environment. This filter maintains a gaze velocity threshold of 100 degrees/s, which allows for smooth pursuit (Bahill & LaRitz, 1984) and vestibular ocular reflexes (Schubert, Migliaccio, & Della Santina, 2006) to be captured as fixations. The software plots a fixation point halfway during the fixation length over the captured HD video. The visual size of the fixation point was chosen to be 1% of the video height, increasing to a maximum of 5% after a 1 s fixation duration. If a fixation point fell into an Area of Interest (AoI), it was manually labelled as belonging to that AoI.

For the applied labels, three types of fixations were identified, each corresponding to a number of AoIs:

- In-car fixations, with mirrors and the speedometer as AoI.
- Guiding fixations, which are fixations up to 2 driving seconds in front of the car and are used to guide the vehicle in the lateral position and keep distance (Lappi & Lehtonen, 2013). The corresponding AoIs included the centre of a lane, a car ahead, and tangent points.
- Look-ahead fixations, which are used to identify future actions (Lehtonen et al., 2012; Mennie et al., 2007). For the look-ahead fixations, the first author conducted a first round of labelling derived from the literature mentioned in the introduction. This led to several

ambiguous labels, including overlapping ones, which were discussed among all authors. Based on this discussion, the authors defined a labelling hierarchy including three subgroups of AoIs relevant for look-ahead fixations:

- The first group of AoIs contained parallel edges to the curve. Using these parallel edges as a discriminatory element adheres to Gestalt grouping principles (Čičković, 2016; Geisler, Perry, Super, & Gallogly, 2001; Wagemans et al., 2012), which suggest that drivers heuristically use parallel edges to the actual curve, to anticipate the curve. Parallel edges were defined as solid edges that included noise barriers and guardrails, or more jagged edges, such as a treeline.
- If a fixation did not fall on a clear parallel edge, it was checked whether the fixation fell on objects that were either visually salient or carried information, namely, signs, gantries, or overpasses.
- If the fixation did not fall onto any of these objects, it was labelled based on one of several generic zones, namely, an occlusion point, far zone, the horizon, or the Focus of Expansion (Lehtonen et al., 2012). When a car ahead was further away than 2 seconds from the participant it was not considered a guiding fixation, but rather labelled according to the zone it is located in (e.g., FOE, Far zone, etc.).

Figure 5-4 provides an overview of all AoIs in the hierarchy used during the labelling process; it illustrates that when a fixation overlaps two or more AoI's, the highest AoI in het hierarchy was selected. The full definitions of the corresponding labels are given in Appendix D. The labelling was done using the AoI tool in the Tobii Pro software. The AoI tool statically showed the defined labels as a snapshot and enabled the author to go along the video, fixation by fixation and label the correct AoI. The labelling was done by the first author. Because all fixations were labelled in this process, the reported distributions in the analysis section add up to 100% of the measured fixations.

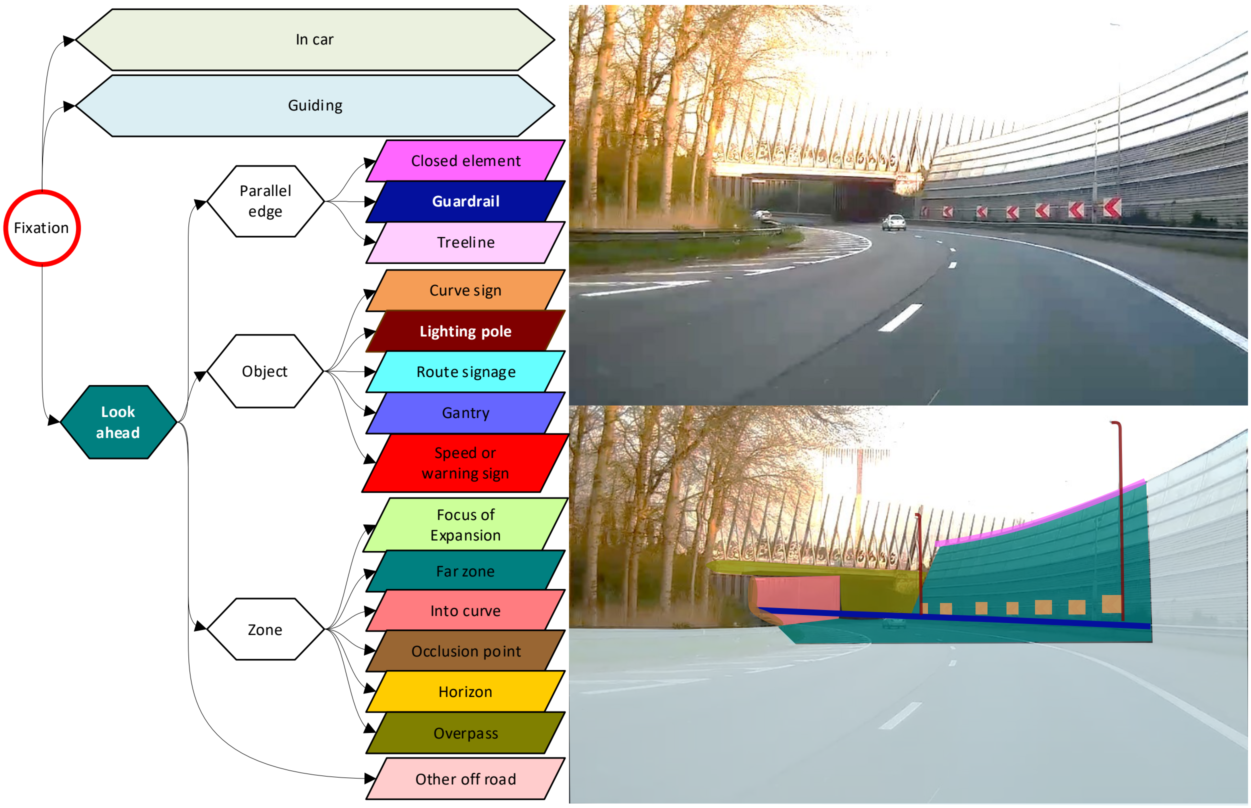


Figure 5-4 Identified Areas of Interest in the labelling hierarchy. On the right, an example of a road view (top) and the corresponding Areas of Interest (bottom).

The timestamps of the fixations were matched with the timestamps from the GPS data. In this way, we were able to position the labelled fixation data both in space and time, that is, relative to the curve start and the start of the deceleration. The fixation durations per AoI were summed up per 50-m sections or per second for analysis in space or time, respectively, in line with the frequency of the GPS tracker, being 1 Hz, and given operational speeds of 30 m/s and an accuracy above 78% within 10 m.

5.2.5.3 Verbal Protocol Analysis

The verbalisations were transcribed verbatim in Dutch and segmented based on mentioned subjects, pauses, or interactions with the experimenter. A segment is defined as a single identifiable unit being a reference, assertion, phrase, thought, or sentence. Each segment was individually labelled. Per segment, a timestamp and English labels were added heuristically by the first author to transform the verbal reports into data on time and subject (Hughes & Parkes, 2003). Additional labels were used per segment to reflect whether the verbal report was retrospective in nature and originated from long-term memory (Ericsson & Simon, 1980) and to reflect the level of driving task the verbal report related to (Michon, 1985). The retrospective segments were omitted from the analysis because these did not reflect the relevant driving task. Driving task levels were labelled "strategic" referring mostly for route choices, "tactical" referring mostly for lane changes, and "operational" referring mostly for speed adjustments. The heuristic labels were discussed among all the authors, focusing on labels deemed ambiguous. The discussion resulted in a detailed description of the labels shown in the Appendix. Based on this detailed description, the first author altered the ambiguous labels accordingly. The following label groups were distinguished:

- Driver-related: reporting on the driving style, operating or maximum speed, familiarity, or comfort.
- Traffic-related: reporting on the traffic surrounding the participant or how the participant interacted with traffic.
- Speed adjustments related to the curve: reporting on decelerating upstream of the curve or accelerating out of the curve.
- Curve-related: reporting on curve sighting, anticipation, and signs.
- Other cues: reporting on the general characteristics of the road and its environment; these could be cues for curves, such as the type of road, number of lanes, or route signage.
- Non-speed-related: a residual group used to label all non-speed-related verbal reports.

Examples of verbal feedback in this paper were translated into English by the first author.

5.3 Results

5.3.1 Task load

The results of the NASA-TLX task load scores before and after the experiment were compared to assess the difference in task loads between normal driving (i.e., driving to arrive at the experiment location) and driving during this experiment. Temporal demand during normal driving (median = 25, *SD* = 21) was significantly higher, $t(30) = 3.16$, $p = 0.004$, than the temporal demand during the experiment (median = 10, *SD* = 14). According to six participants, the setting of the experiment was more relaxed compared to the normally rushed driving on a freeway, which could explain the above difference in temporal demand. The effort during the experiment (median = 20, *SD* = 17) was significantly higher, $t(30) = -2.29$, $p = 0.029$, than the effort during normal freeway driving (median 15, *SD* = 11). Five participants mentioned the extra effort of wearing the eye-tracker during the experiment. No significant differences were observed in mental demand, physical demand, performance, or frustration between normal driving and driving during the experiment.

5.3.2 Fixation duration

The eye-tracker recordings of one participant were not saved correctly, one participant appeared to be near-sighted, and two calibrations were questionable. The entire measurements from these four participants were omitted from the database. The remaining 27 measurements were further analysed. During the experiment several days were rather sunny. The sun interferes with the infrared illuminators of the eye-tracker, resulting in poor eye-tracking or no measurements at all because of squinting eyes in several individual curves per participant. These individual curves were omitted from the database. All of the above resulted in 22 successful recordings for Curves 1 and 4b, 21 successful recordings for Curve 2, and 23 successful recordings for Curves 3, 4a, and 5.

The median fixation duration of all fixations was 240 ms (*SD* = 557 ms). In-car fixations, guiding fixations, and look-ahead fixations had a median duration of 240 ms (*SD* = 208 ms), 281 ms (*SD* = 624 ms), and 220 ms (*SD* = 575 ms), respectively.

5.3.2.1 Distribution of fixation duration towards curve start

The distribution of fixation duration of all participants and curves from 550 m before to 250 m after the curve start is shown in Figure 5-5. The participants spent about 40% of the time on look-ahead fixations in the curve approach and curve entry. A Wilcoxon signed-rank test indicated that the number of look-ahead fixations 550 m before the start of the curve (median = 40%) and 150 m after the start of the curve (median = 36%) was not statistically significantly different (p = 0.222, r = 0.106); for this comparison, 150 m was used, as for the shortest curve (Curve 5) fixations beyond that point could also be assigned to tangents or curve approach of a second curve.

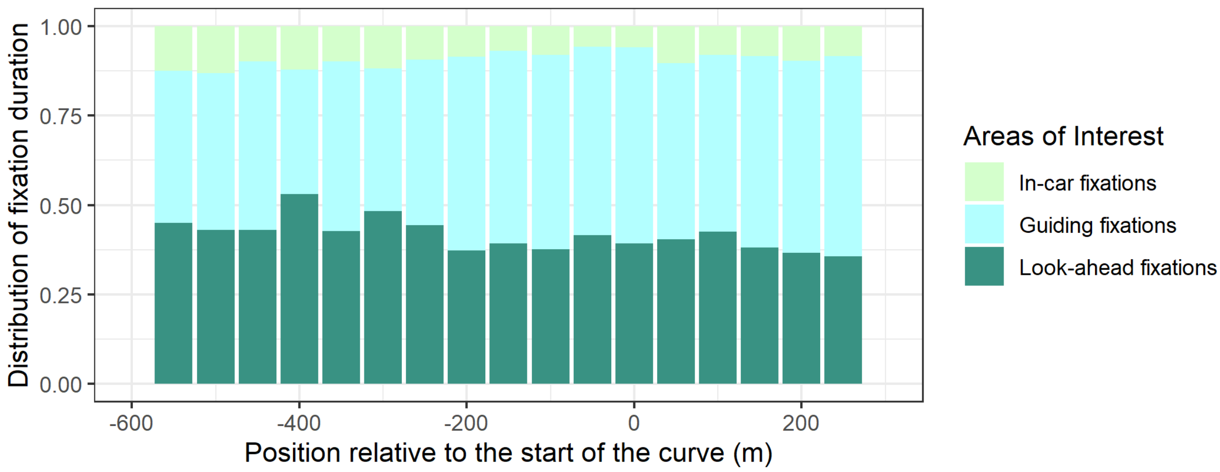


Figure 5-5 Distribution of fixation duration of all curves and all participants relative to the start of the curve.

Figure 5-6 zooms in on the distribution of look-ahead fixations around the start of the curve. A transition zone between 300 m and 100 m upstream of the curve is visible, where fixations shifted from the Focus of Expansion, route signage, and speed or warning signs to the far zone, parallel edges (closed elements, guardrail, and treelines parallel to the curve), and curve signs.

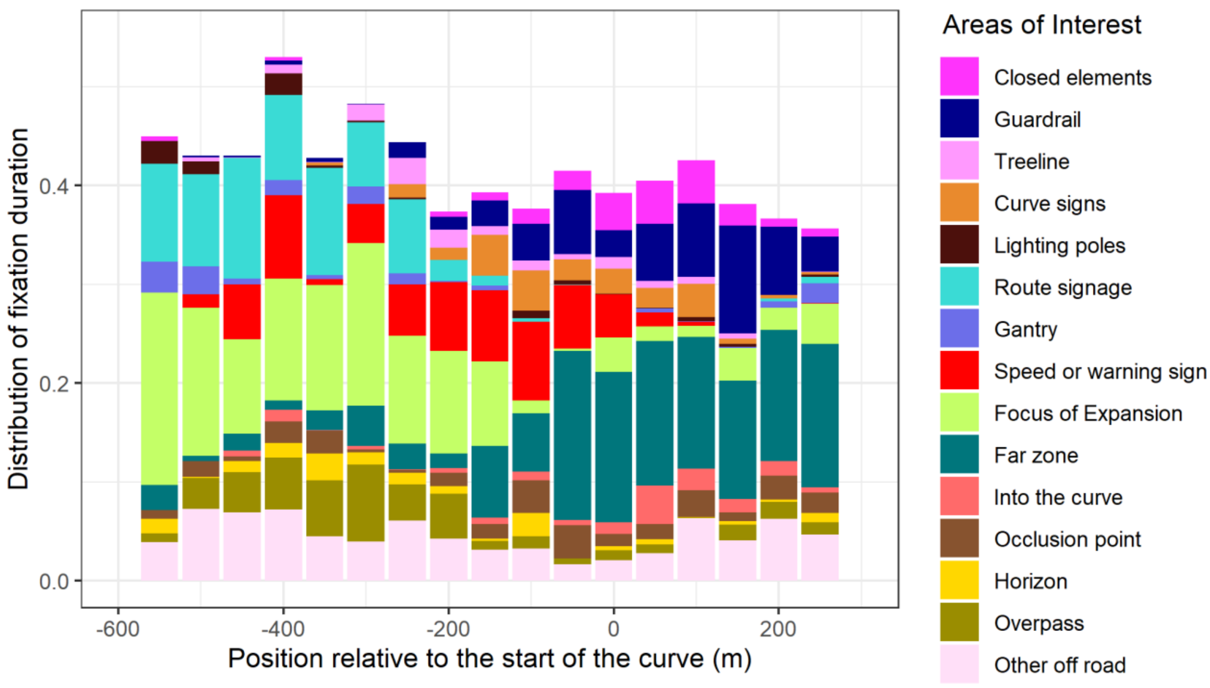


Figure 5-6 Distribution of fixation duration for look-ahead fixations of all curves and all participants, relative to the start of the curve.

5.3.2.2 Distribution of fixation duration towards deceleration

Figure 5-7 shows the distribution of fixation durations from 20 s before to 20 s after the participants started to decelerate. No change in look-ahead fixations is observed before, around, or after the start of deceleration. A Wilcoxon signed-rank test indicated that the number of look-ahead fixations 20 s before the start of deceleration (median = 39%) and 20 s after the start of deceleration (median = 46%) was not statistically significantly different (p = 0.951, r = 0.006).

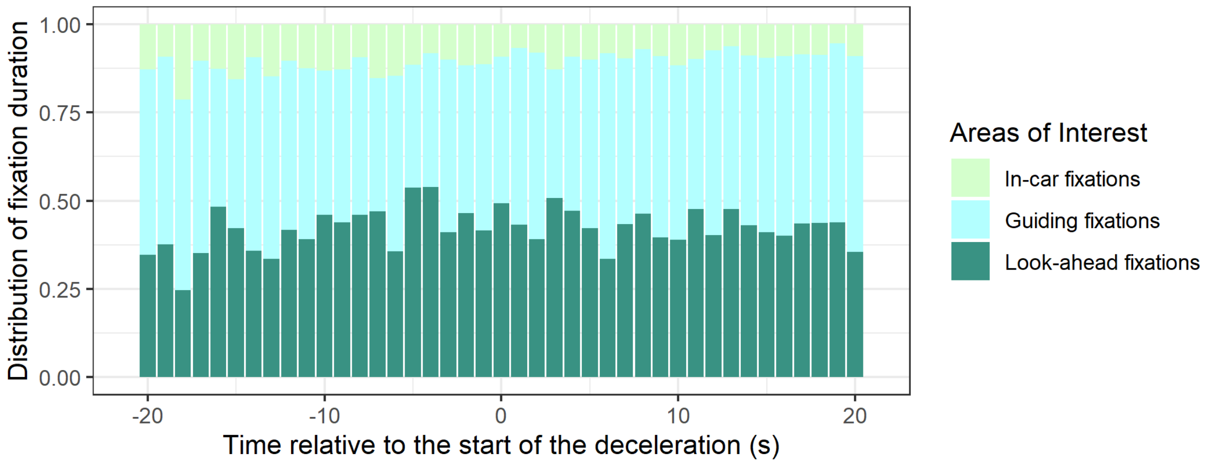


Figure 5-7 Distribution of fixation duration of all curves and all participants, relative to the start of deceleration.

Figure 5-8 zooms in on the distribution of look-ahead fixations around the start of deceleration. Until about 3 s prior to the start of deceleration, participants focused mainly on the Focus of Expansion and route signage. The latter might due to the experimental setup, where the experimenter pointed out route signage for route directions. A small increase in fixations on the Focus of Expansion is seen 4 s before the start of deceleration. Furthermore, it is noticed that when drivers started to decelerate, they fixated less on the Focus of Expansion and more on the far zone and parallel edges (closed elements, guardrail, and treelines parallel to the curve). An increase in fixations on speed signs or warning signs is only noticeable after the deceleration has started.

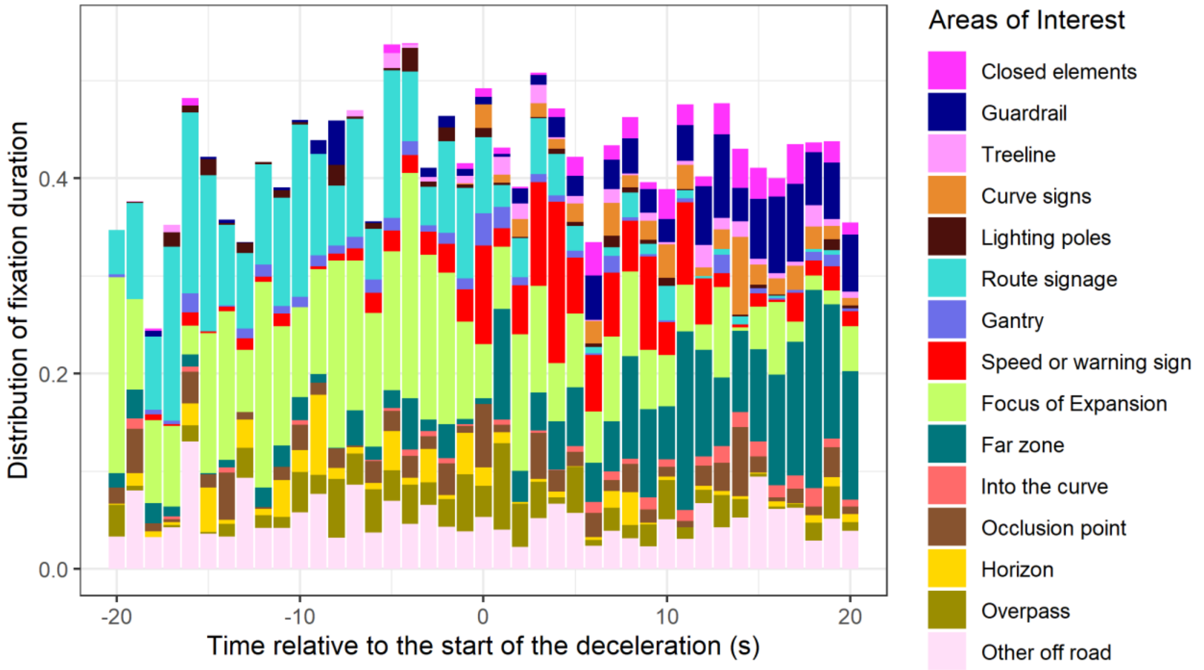


Figure 5-8 Distribution of fixation duration for look-ahead fixations of all curves and all participants, relative to the start of deceleration.

5.3.2.3 *Distribution of fixation duration in individual curves*

Each of the investigated curves had a unique layout; therefore, unique driving behaviour was expected. An average speed profile of all participants, the fixation duration, and the start of deceleration distribution per curve are shown in individual figures.

Curve 1 shows in Figure 5-9 a rather sudden change in look-ahead fixations around 200 m before the curve. This is likely due to the end of the noise barrier, which obstructed the view towards the speed sign and the far zone of the curve itself. Participants showed more interest in the occlusion point in Curve 1 than in the other curves. Most participants started to decelerate before fixating on the speed sign.

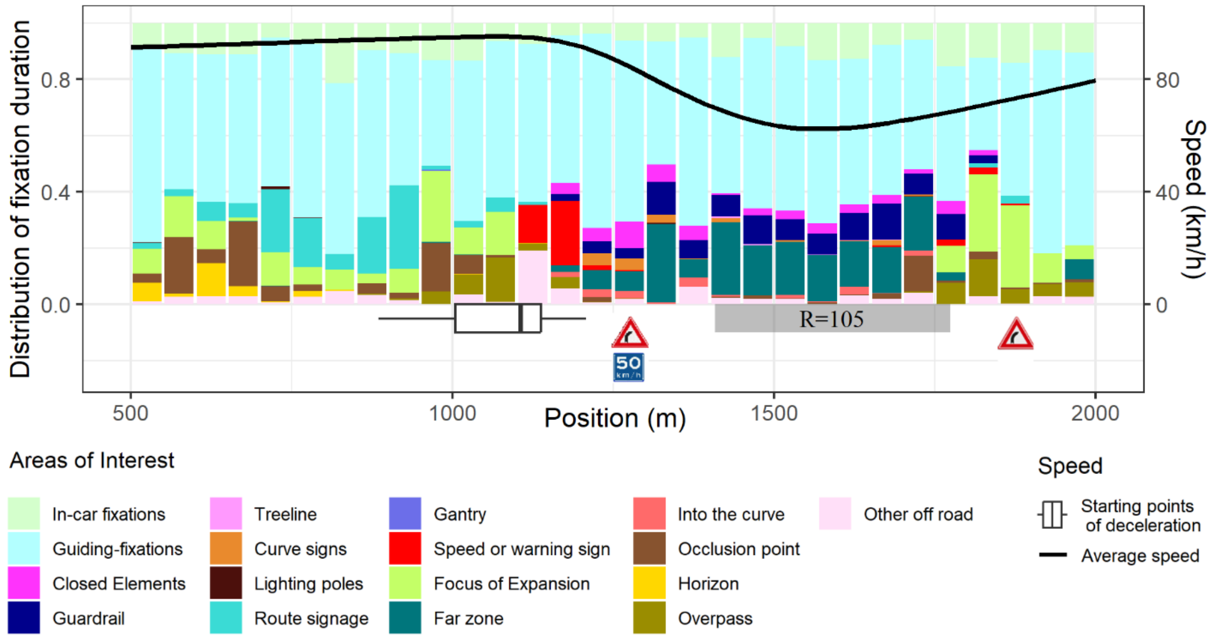


Figure 5-9 Average speed behaviour, distribution of fixation duration, and start of deceleration distribution of Curve 1, having a horizontal radius of 105 m. The positions of the curve is indicated with a grey box and the positions of speed and warning signs are also indicated.

Curve 2 was positioned at the end of a main carriageway; therefore, there were many speed and warning signs present before the curve, since such a sharp curve is not expected in a main carriageway. As seen in Figure 5-10, most participants started to decelerate after fixating on the first speed and warning sign. At the positions where most decelerations started, an equal amount of time was dedicated to the warning signs and the Focus of Expansion. Only after the deceleration started participants fixated on the parallel edges or the far zone.

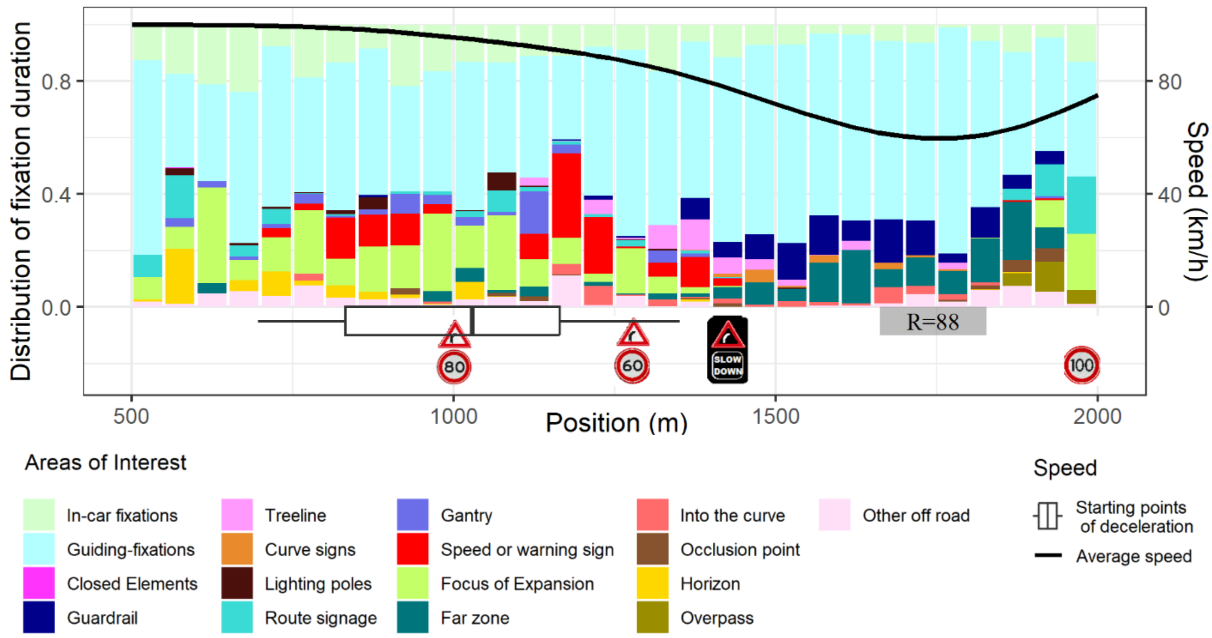


Figure 5-10 Average speed behaviour, distribution of fixation duration, and start of deceleration distribution of Curve 2, having a horizontal radius of 88 m. The positions of the curve is indicated with a grey box and the positions of speed and warning signs are also indicated.

Curve 3 shows in Figure 5-11 an increase in fixation towards the Focus of Expansion and the warning signs just before most participants started to decelerate. After the deceleration started, the attention shifted towards the occlusion point, far zone, and less towards the focus of expansion. The warning sign on Curve 3 is located just in front of the overpass, obstructing most of the curve. Since only guardrails are present as a parallel edge, not many fixations are given on parallel edges, but more on the far zone.

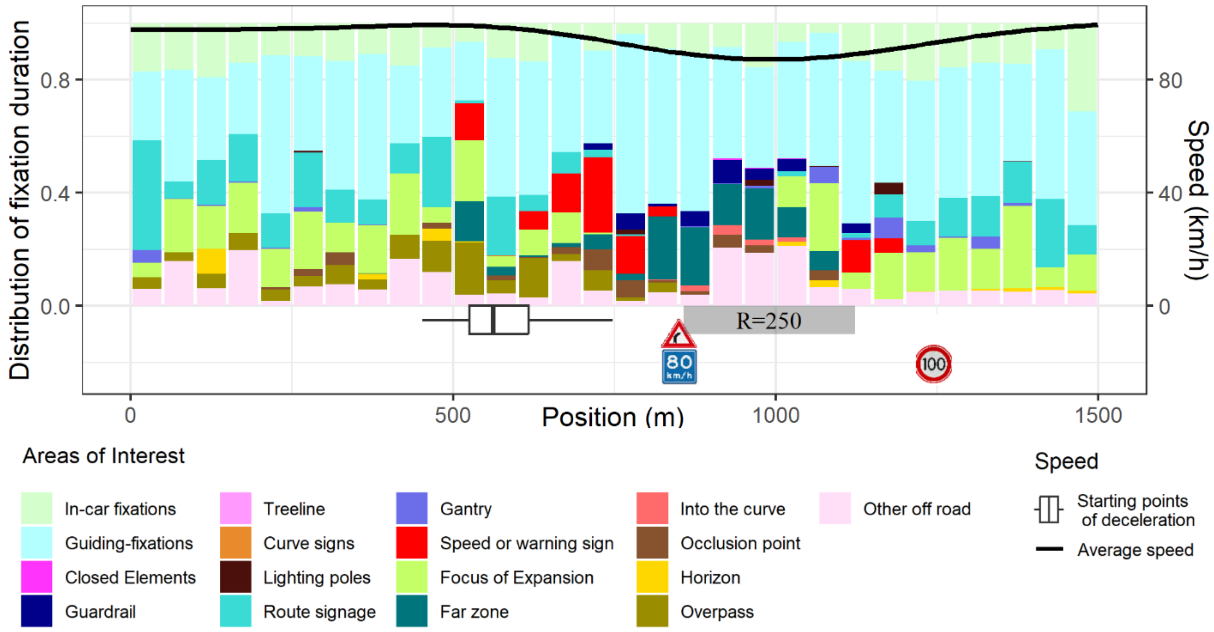


Figure 5-11 Average speed behaviour, distribution of fixation duration, and start of deceleration distribution of Curve 3 having a horizontal radius of 250 m. The positions of the curve is indicated with a grey box and the positions of speed and warning signs are also indicated.

Curve 4a shows in Figure 5-12 that most participants started to decelerate before fixating on the speed sign. A few look-ahead fixations towards a far zone were observed because this curve was clearly in sight and moved over the main carriageway. Curve 4b shows in Figure 5-13 an increase of fixations towards the warning sign before most participants started to decelerate. Only after starting to decelerate the curve signs (chevrons) were fixated on. Again, this curve was mostly obscured by an overpass.

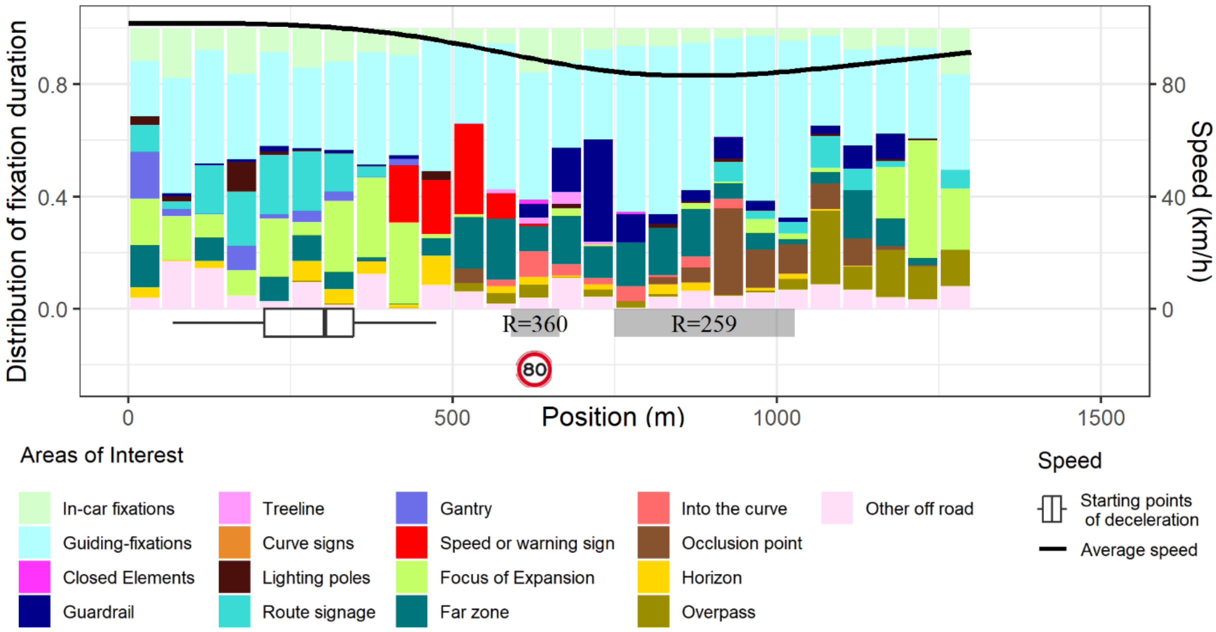


Figure 5-12 Average speed behaviour, distribution of fixation duration, and start of deceleration distribution of Curve 4a, having a horizontal radius of 360 m. The positions of the curve is indicated with a grey box and the positions of speed and warning signs are also indicated.

Figure 5-13 Average speed behaviour, distribution of fixation duration, and start of deceleration distribution of Curve 4b, having a horizontal radius of 128 m. The positions of the curve is indicated with a grey box and the positions of speed and warning signs are also indicated.

Curve 5 was the first, short, curve of a set of curves in a junction. Deceleration before these curves was preceded only by fixations towards the Focus of Expansion and route signage, as showed in Figure 5-14. No warning signs were present before the first curve to fixate upon.

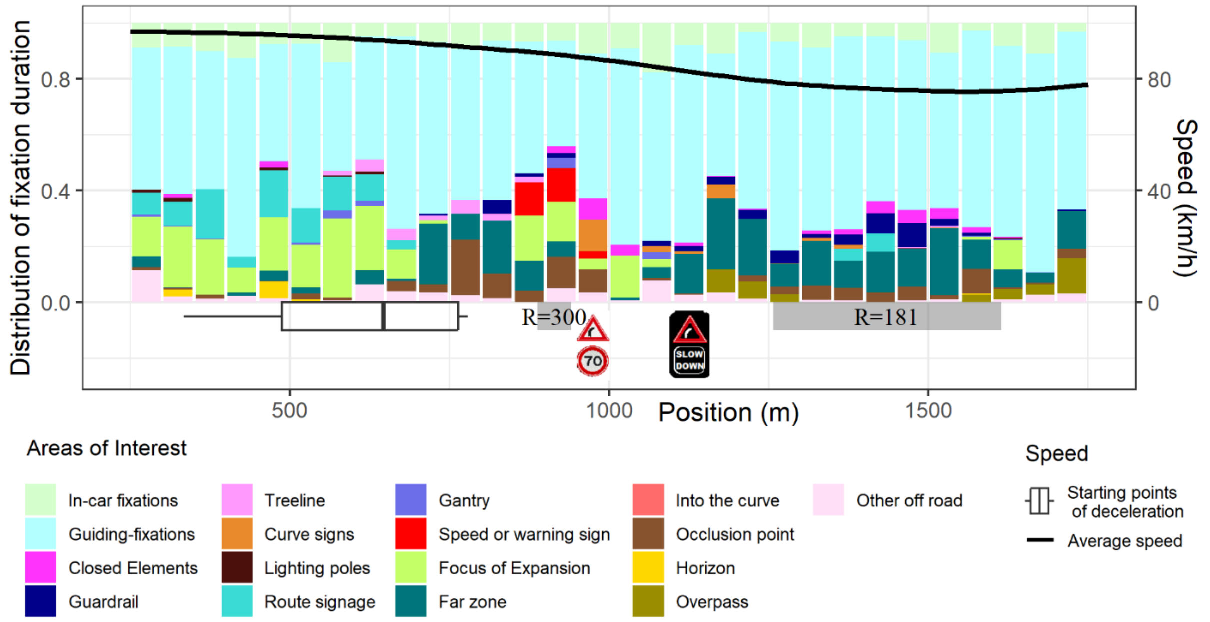


Figure 5-14 Average speed behaviour, distribution of fixation duration, and start of deceleration distribution of Curve 5, having a horizontal radius of 300 m. The positions of the curve is indicated with a grey box and the positions of speed and warning signs are also indicated.

5.3.2.4 *Effects of familiarity*

The participants scored their familiarity in Curve 1 on average 4.8 (SD = 3.1), in Curve 2 on average 5.6 (SD = 3.6), in Curve 3 on average 5.4 (SD = 3.1), in Curve 4a and 4b on average 3.1 (SD = 2.6) and in Curve 5 on average 5.7 (SD = 3.3). Familiarity was not correlated to the position where participants in free-flow situations started to decelerate. Familiarity showed however weak positive relationships with speed at curve start in free-flow situations. Pearson's correlation coefficients ranging from $r(10) = 0.03$, $p = 0.91$ in Curve 5 to $r(25) = 0.46$, $p = 0.02$ in Curve 4a indicate higher speeds with higher familiarity of a curve. For each participant, the relative amount of fixation duration towards specific Areas of Interest were tested on correlation. Familiarity has a weak negative relationship to the relative look-ahead fixation duration ($r(22) = -0.32$, $p = 0.13$), and a negative relationship towards the relative fixation duration towards parallel edges (closed elements, guardrails and tree lines) ($r(22) = -0.36$, $p = 0.08$). There was no relationship between Familiarity, on the one hand, and fixations on curve signs, speed/warning signs, Focus of Expansion, or the far zone, on the other.

5.3.3 Verbalisation

The participants were verbalising their operational driving task on average 22% (SD = 19%) of the total time while driving on the sections of the road investigated. Verbalising the tactical and strategic driving tasks took up on average 4% (SD = 7%) and 4% (SD= 5%) of the driving time respectively, while on average 10% (SD= 16%) of the time was spent verbalising on non-driving task topics. For each of the labels defined in the Appendix, Table 5-1 shows how many times each topic was verbalised. In total, 1301 verbalisation segments were labelled. Since each segment can have multiple labels, the percentages given in Table 5-1 reflect the percentage of segments containing these labels. A large number of verbalisations were related to the driver and surrounding traffic, and only about 30% of the verbalisations were related to the curve. Out of the verbalisations related to the curve, most were on decelerating for the curve.

Table 5-1 Summary of verbalisations related to speed. In bold, the group totals, and bullet-wise the individual labels are shown

	%	N		%	N
Driver-related	***23.1%***	***300***	***Curve-related***	***11.7%***	***152***
• Driving style	5.5%	72	• Curve sighting	5.1%	67
• Operating speed	3.5%	46	• Anticipating radius	5.1%	66
• Faster than speed sign	4.5%	60	• Anticipating length	0.7%	9
• Slower than speed sign	0.2%	3	• Curve direction	1.2%	15
• Unsure about max speed	0.5%	6	• Curve end	0.3%	4
• Comfort	4.6%	63	• Oversight	0.8%	10
• Familiarity	5.7%	75	• No oversight	0.9%	12
			• Speed sign	8.4%	109
			• Trees	0.0%	0
			• Warning sign	0.7%	9
			• Curve sign (chevron)	0.2%	2
Traffic-related	***20.3%***	***265***	***Other cues***	***2.9%***	***38***
• Cars braking	1.8%	23	• Type of road	1.2%	15
• Traffic volume	2.0%	26	• Number of lanes	0.6%	8
• Adjust to traffic	9.0%	117	• Lane ending	0.8%	10
• Overtaking	3.8%	50	• Special marking	0.0%	0
• Pre-sorting	4.3%	56	• Route signing	0.5%	6
• Lane-keeping	0.4%	5	• Overpass	0.0%	0
Speed-related to curve	***18.9%***	***246***	***Not related to external speed cues***	***26.4%***	***343***
• Decelerating for curve	12.8%	167			
• Accelerating after curve	6.2%	81			

Some participants mentioned that it was hard to verbalise the anticipation of a curve because it is such a natural or logical thing to do. Participant 1 said, for example: *"I'm reducing speed for a curve, but that goes without saying, right?"*.

5.3.3.1 Co-occurrence with deceleration

As seen in Table 5-1, decelerating for a curve was mentioned 167 times during the experiment. Sometimes the participant elaborated further on the specific cue or reason, which led to multiple assigned labels per segment (co-occurrence in labels). Since the aim of this research is to understand which cues drivers use to decelerate, co-occurrence with the verbalisation of decelerations is further researched. Table 5-2 shows the distribution among the different labels that co-occurred with the label of deceleration for a curve in a single verbalisation segment. Out of the 167 verbalisations of deceleration for a curve, 92 did not co-occur with other labels (55%) and gave, therefore, no specific cue for deceleration for a curve. Table 5-2 shows the distribution of the remaining 45% of verbalisations.

Table 5-2 Co-occurring labels along verbalising "decelerating for a curve". In bold, the group totals, and bullet-wise the individual labels are shown.

	%	N
Driver-related	***10.2%***	***17***
• Driving style	1.2%	2
• Operating speed	0.6%	1
• Faster than speed sign	1.2%	2
• Comfort	4.8%	8
• Familiarity	2.4%	4
Traffic-related	***3.6%***	***6***
• Cars braking	1.8%	3
• Adjusting to traffic	1.2%	2
• Overtaking	0.6%	1
Curve-related	***34.1%***	***57***
• Curve sighting	12.0%	20
• Anticipating radius	11.4%	19
• Anticipating length	0.6%	1
• Curve direction	0.6%	1
• No oversight	1.8%	3
• Speed sign	13.2%	22
Other cues	***0.6%***	***1***
• Road type	0.6%	1

Table 5-2 shows that most of the co-occurring labels with "decelerating for a curve" were towards speed signs, seeing the curve itself, and anticipating its radius. In addition to the reasons mentioned in Table 5-2, two participants elaborated in retrospective verbalisations on using on-board navigation systems with a map to anticipate an upcoming curve.

5.3.3.2 Sign verbalisation

Table 5-1 shows that speed signs were verbalised ten times more than warning signs and that curve chevron signs were seldom mentioned. Warning sign labels co-occurred in a verbalisation segment only once with a curve sighting label and three times with a speed sign label. Speed sign labels co-occurred four times with curve sighting labels, and warning sign labels co-occurred only once with curve sighting labels. A number of participants verbalised speed signs just after verbalising curve discovery:

- *"I'm decelerating because I see an upcoming curve, would have done that even without the speed sign"* (Participant 1)
- *"A sharp curve here, designated with a 80 km/h sign and a warning sign"* (participant 5)
- *"I don't want to drive too fast with this upcoming curve. And indeed, a warning sign "you are driving too fast", so… I'm going to adjust my speed to the other traffic"* (Participant 11)
- *"But this is a curve with an advisory speed of 50 km/h, so I'm going to brake harder"* (Participant 25)

Verbalisations of speed signs both mention following up the speed on the sign and not. A couple of examples are:

- *"80 km/h, but I'm driving 100 km/h still, so I'm driving a bit too fast, but this is well suited for 100 km/h"* (Participant 5)
- *"I'm seeing a sign 70 km/h, I think, well, let's release gas."* (Participant 8)
- *"I've seen the advisory speed sign 80 km/h but chose not to comply because it's wide enough, sunny and the road surface looks good"*. (Participant 11)

- *"Well, we're allowed 80 km/h and approaching with 120 km/h. That curve is perfectly suited for 110 km/h. I don't understand that sign".* (Participant 15)
- *"Oh, there it becomes 50 km/h, so, let's slow down."* (Participant 17)
- *"Advisory speed 50 km/h. Let's see what my predecessors do. They don't brake a lot, so I think 70 km/h is a nice speed. A sharp curve, so I'm slowing down. This is a good speed."* (Participant 20)
- *"I see 50 km/h here, so, eh. Advisory speed, so let's adhere to that".* (Participant 23)
- *"I'm releasing gas now; it said 80 km/h".* (Participant 28)

No specific verbalisations towards the use of the Focus of Expansion, parallel edges, or far zones are given.

5.3.4 Participant feedback on speed reduction before curve

After revealing the aim of the experiment in the post-experiment questionnaire, several participants shared their insights into how they reduced speed before a curve in the final questionnaire. Four participants mentioned that all curves had different signs, but only three others shared that they did use signs to anticipate their speed. Participant 4 actually shared a description of curve approach: *"I follow the traffic in front of me. I reduce speed upon seeing a speed sign. In a regular situation, I tend to brake as less as possible. I then judge the curve on sharpness, clarity, traffic volume and speed".* Overall, 20 participants could not give insights into how they reduce speed before a curve in the post-experiment questionnaire, indicating unawareness.

5.4 Discussion and limitations

The main aim of this research was to gain insights into which visual cues drivers use to reduce speed upon approaching a curve. By combining speed data and look ahead-fixations, we found that the participants tended to start decelerating about 4 seconds after look-ahead fixations on the Focus of Expansion increased and that fixations on speed and warning signs are mostly manifested after the start of deceleration. Towards the curve start, fixations towards parallel edges (closed elements, guardrail or treelines parallel to the curve trajectory) and into the curve itself are increased, and fixations on the Focus of Expansion are decreased. These findings deviate from driving task descriptions (Campbell et al., 2012; McKnight & Adams, 1970), which position the gathering of speed information from signing at the same time of initial speed reduction and as one of the primary speed influences. We conclude that the curve discovery on the Focus of Expansion itself provides enough visual information to start reducing speed. We therefore diminish the usually suggested importance of signs for curve anticipation (Borowsky, Shinar, & Parmet, 2008; Campbell et al., 2012; Costa et al., 2022; Fitzpatrick, Carlson, Brewer, & Wooldridge, 2003; Montella, Galante, Mauriello, & Pariota, 2015). Verbal feedback confirmed that speed signs are used to assess the needed speed reduction better, knowing that the speed indicated on the signs can usually be exceeded. This non-compliance is in line with Ahie, Charlton, and Starkey (2015).

The reported large amount of fixations on the Focus of Expansion on tangents are in line with previous research (Lehtonen et al., 2012; Salvucci & Gray, 2004; Shinar et al., 1977). The increased amount of fixations on the Focus of Expansion before the start of deceleration might indicate that participants used a change in the optical flow near the Focus of Expansion (Rogers, 2021) or the presence of a kink in the road trajectory (Brummelaar, 1975) as a first indicator of the curve itself, which is in line with Gestalt grouping principles (Čičković, 2016). No verbal reports on this first curve discovery were made, suggesting highly automated responses. Similarly, most participants could not actively answer the post-experiment question on their speed-adjusting behaviour in curve approach, underpinning the unawareness and skill-based nature of this driving task. Towards the start of the curve, fixations on the Focus of Expansion diminished in favour of fixations on parallel edges and the far zone, not being the occlusion point per se (Lehtonen et al., 2012), suggesting that the participants anticipated the curve sharpness mostly based on the available information in their field of view. We furthermore found a fairly stable amount of look-ahead fixations of 39–44 % of the time during curve approach, while earlier research reported 10–33 % (Lehtonen et al., 2013). This difference might be because Lehtonen et al. (2013) defined look-ahead fixations as being outside the 6-degrees field of view, while we labelled it based on the contents in the Area of Interest.

A large proportion of verbal reporting was devoted to speed signs, which might be due to the task to verbalise speed behaviour. Curve 2, however, demonstrates how warning signs are used as the main cue to start deceleration when the curve is in the main carriageway, on which no such sharp curve is expected, while there are no good parallel edges available. The large amount of fixations on the route signage reported might be due to the experimental setup, where the experimenter gave route directions orally by pointing out directions on the route signage.

Familiarity of participants with specific curves, resulted in higher speeds, which is in line with the finding by Pratt et al. (2019). Furthermore, familiarity of curves led to less time spent on look ahead fixations in general and towards parallel edges (closed elements, guardrails and tree lines) in general. These findings are in line with findings by Young et al. (2018), showing more fixations on the road far ahead with less familiarity. Only 16% of the participants were female, so our results may be skewed towards male speed and fixation behaviour.

Think-aloud methods might interfere with natural driving behaviour (Salmon et al., 2017; Thomas, Goode, Grant, Taylor, & Salmon, 2015) or looking behaviour (Prokop, Pilař, & Tichá, 2020) and might make participants more aware than they would be in everyday driving. To investigate the effect of the think-aloud protocol on the participants' behaviour, a pilot study was conducted prior to the experiment in which four test participants (2 male, 2 female, average age of 45 years, average amount of driving experience of 24 years) drove the proposed route twice. On the first drive, two participants were asked to engage in concurrent think-aloud, and the other two were asked to drive without concurrent think-aloud. The second drive was vice versa. Comparing the collected data from sessions with and without concurrent think-aloud did not show major differences in speed, deceleration, fixation lengths or distribution. Therefore, concurrent think-aloud was applied to understand which visual cues were used by the participants to reduce speed (Ericsson & Fox, 2011). Retrospective think-aloud might have given more insights (Stapel, El Hassnaoui, & Happee, 2020) than concurrent think-aloud, but it would not be possible to stop on a freeway, and memory decays after two minutes. The task-load comparison between pre-experiment and post experiment, and the post-experiment questionnaire did not show signs that the verbalisation interfered with the natural driving task.

Eye-tracking does not provide information on the role of peripheral vision in anticipating speed (Martens, Comte, & Kaptein, 1997) and in helping to focus on relevant information (Wolfe, Sawyer, & Rosenholtz, 2022). It can, however, be argued that the relevant visual information is attended to with a fixation on the fovea (Crundall & Underwood, 2011). Furthermore, our research focusses on look-ahead fixations, which generally are not in the periphery but at least 50 m and up to 500 m in front of the driver. At the same time, these large distances are a downside in this research, as at such distances, the HD video does not show details that the human eye might perceive, making the labelling of Areas of Interest ambiguous. Therefore, labels at the horizon, Focus of Expansion, or far zone might have been overrepresented in this research.

5.5 Conclusions and implications

By using three different methodologies, GPS, eye-tracking, and think-aloud, we were able to gain insights into which visual cues drivers use to reduce speed upon approaching a freeway curve. We used the qualitative data gathered from the verbal protocol to support and interpret the quantitative analysis from GPS and eye-tracking.

The results showed that participants used the Focus of Expansion and parallel edges as a first cue to start decelerating before a curve. When this visual information was not sufficiently available participants used warning and speed signs as a first cue. Speed signs were generally used in a confirmatory manner or to update speed anticipation.

The results support the self-explaining nature of freeways and imply that when deceleration is needed based on the geometric design, extra attention should be paid to the road layout and its surrounding so that it provides enough information to the drivers about an upcoming curve. This could be done by using parallel edges. Speed and warning signs can be used when the road layout is unclear, such as when parallel edges are obstructed or absent. Further research is needed to understand the situations in which extra signs are needed and on which exact position to place them, to match the expectations of drivers.

6 A Bayesian Belief Network to Mimic Driver Expectations in Curve Approach

This chapter is currently under review for journal publication: ***Vos, J.***, *Farah, H., & Hagenzieker, M. (under review). Modelling Driver Expectations for Safe Speeds on Freeway Curves using Bayesian Belief Networks*

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 from a distance. Therefore, drivers are believed to use other cues to decide on decelerating 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. Our aim is to model these expectations and use them pro-actively in freeway design and safety assessment. 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. The drivers are assumed to adjust their operating speeds if it doesn't 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. Both the preceding type of roadway and the number of lanes are also important cues to set the 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 together with the road scene upstream of the curve.

6.1 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 et al., 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 & 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 & 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 & 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 model for expected safe speeds during curve approach to be usable 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 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.

6.2 Literature review

6.2.1 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 (Altamira et al., 2014; Malaghan et al., 2021; Nama et al., 2020; Vos & 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, 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; A. Montella et al., 2015). Driving task analysis research has resulted in descriptions of how drivers anticipate and approach a curve (Campbell et al., 2012; McKnight & 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.

6.2.2 Curve perception and speed reduction

Both the driving task descriptions, and a recent eye-tracking experiment which captured anticipatory fixations during curve approach (Vos, de Winter, Farah, & Hagenzieker, 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 1970s the road picture of curves as it is perceived by the driver was analysed using perspective drawings with sets of hyperbola (Springer & 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:

$$Z^2 = R_h(46h\text{-}2a) \qquad [6\text{-}1]$$

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 6-1 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 6-1 can also be used to alter the height of the road edge, and thus of a parallel edge. Figure 6-1 shows the sight line as intended in equation 6-1, and the sight line used to calculate the height of a parallel edge. If an eye-height of 1.1 meters above the road is used, a parallel edge of 2.2 meters 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 6-1. So, if a distance of 5 meters from the driver to the parallel edge is set, equation 6-1 can be used to see what the effects of different heights of parallel edges are on what drivers perceive. This is shown in Figure 6-1 using different lines for different heights. Figure 6-1 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):

$$posBP1 = 155 * \ln(R_h) - 1067 \qquad [6\text{-}2]$$

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

Equation 6-2 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.

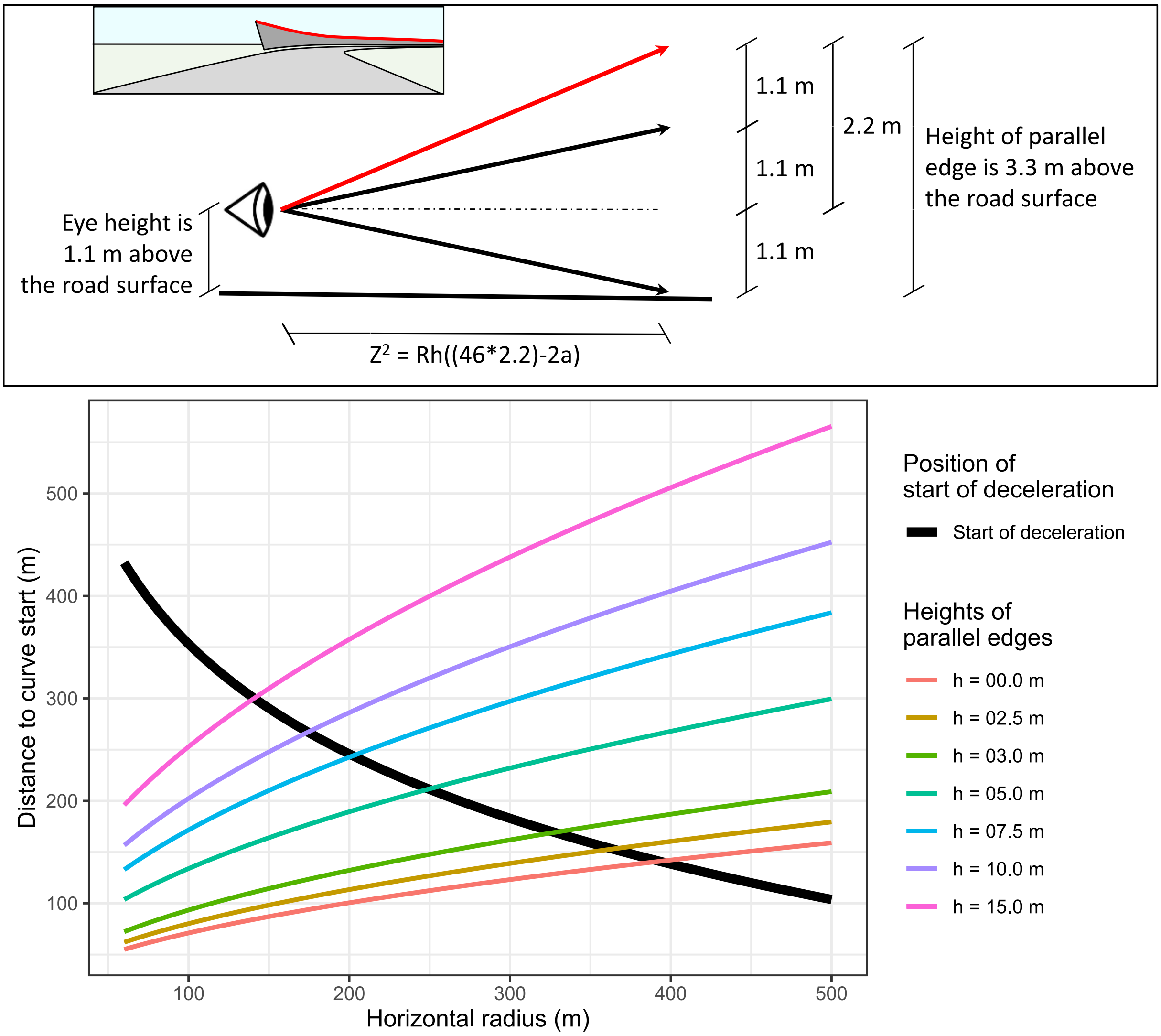


Figure 6-1 Analysing the perception of parallel edges in curves regarding their height. The top panel shows how equation 1 is used to calculate from which distance Z a curve shows its curvature to drivers, based on the height of a parallel edge. The red line shows the edge of a noise barrier as an example. 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.

Combining equations 6-1 and 6-2 in Figure 6-1 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 meters, 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 meter, a parallel edge with a height of 3 meters would show the curvature to drivers before starting to decelerate, but for a radius of 200 meters, a parallel edge of 7.5 meters is needed. It is unlikely that parallel edges this high are available. So, particularly for curves with radii of 300 meters 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.

6.2.3 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) based on what people have learned to expect (Theeuwes, Horst, & Kuiken, 2012). These expectations are based on the development of mental categories, or schemata, containing curve cues and corresponding safe speeds (Charlton & Starkey, 2017b), which are built upon multiple episodes (Ghosh & Gilboa, 2014). In human information processing models (Wickens et al., 2021), schemata reside in the long term memory (Plant & Stanton, 2013) and therefore act as input for the working memory to select the correct response based on perception as is illustrated in Figure 6-2. 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 & Starkey, 2017a, 2017b; Ranney, 1994).

6.2.4 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, Graves, & Turk-Browne, 2020). Statistical learning is thought of as a cognitive mechanism to discover underlying structures and distributions of these perceptual cues and their distributions (Frost, Armstrong, Siegelman, & Christiansen, 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 & Tenenbaum, 2006; Seriès & Seitz, 2013). It has furthermore been found that drivers also learn these regularities and differences for spatial navigation (Chanales, Oza, Favila, & Kuhl, 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, Kemp, Griffiths, & Goodman, 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. Figure 6-2 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.

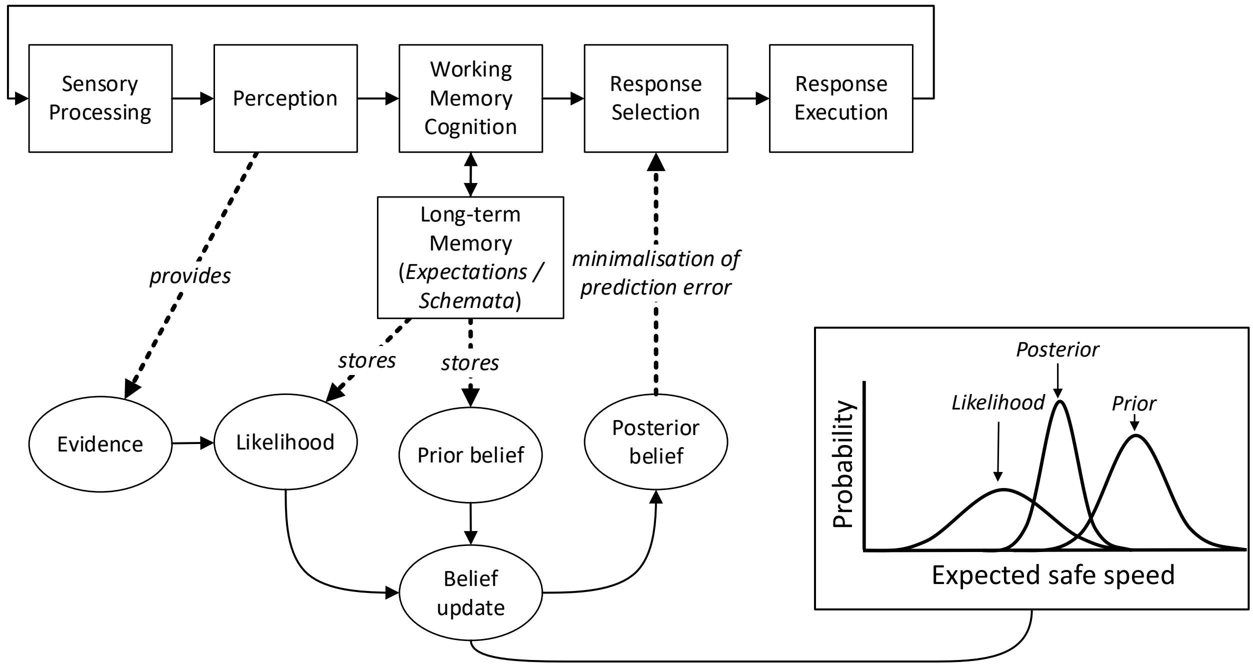


Figure 6-2 Human information processing (squares) and Bayesian belief updating (ovals) with assumed connections in dashed arrows. The model of information processing is simplified from Wickens et al. (2021) and includes the notion that schemata reside in long term memory (Plant & Stanton, 2013). This 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.

6.2.5 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 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:

$$P(v_i|c) = \frac{P(c|v_i) \cdot P(v_i)}{P(c)} = \frac{P(c|v_i) \cdot P(v_i)}{\sum_i P(v_i) \cdot P(c|v_i)} \quad [6\text{-}3]$$

where: $P(v_i\|c)$	=	<u>*Posterior*</u> belief for safe speed given a certain cue
$P(c\|v_i)$	=	<u>*Likelihood*</u> of a cue appearing given a certain safe speed
$P(v_i)$	=	<u>*Prior*</u> belief for safe speed
$P(c)$	=	<u>*Marginal*</u> probability of a cue appearing
$\sum_i P(v_i) \cdot P(c\|v_i)$	=	Sum of (*Prior* * *likelihood*) over all safe speeds

Equation 6-3 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. Figure 6-2 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.

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 Figure 6-3, 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 Figure 6-2. 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 curve (Wilde, 1998) or feelings of discomfort (Summala, 2007).

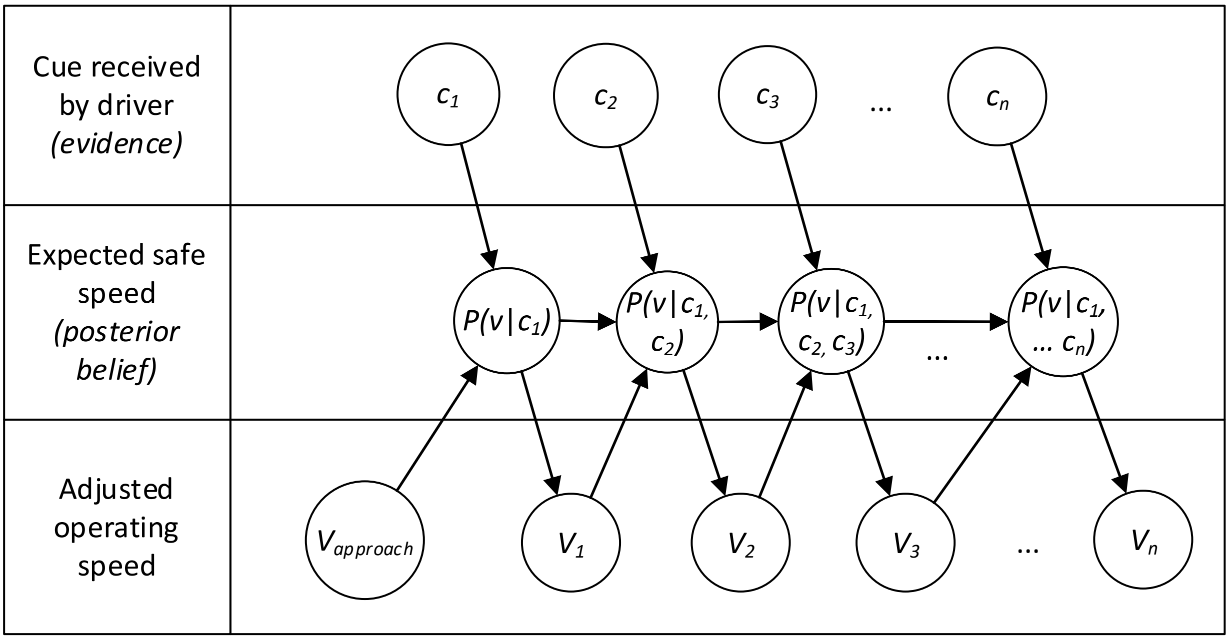


Figure 6-3 The process of updating the expected safe speed in a curve given the received cues (C_1, C_2, C_3, …, C_n) and adjusting the operating speed accordingly.

6.3 Methods

6.3.1 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. This data 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 & 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 6-1 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 de 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. 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 1Hz, 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 median speed driven in those curves.

Table 6-1 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%			

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 6-1. This gives the first probabilistic view on the expected safe speed for different curve cues independently.

6.3.2 Modelling a Bayesian Belief Network

The modelling and analysis was done in the GeNIe Modeler ("GeNIe Modeler," 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 Figure 6-4. 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 6-3. 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.

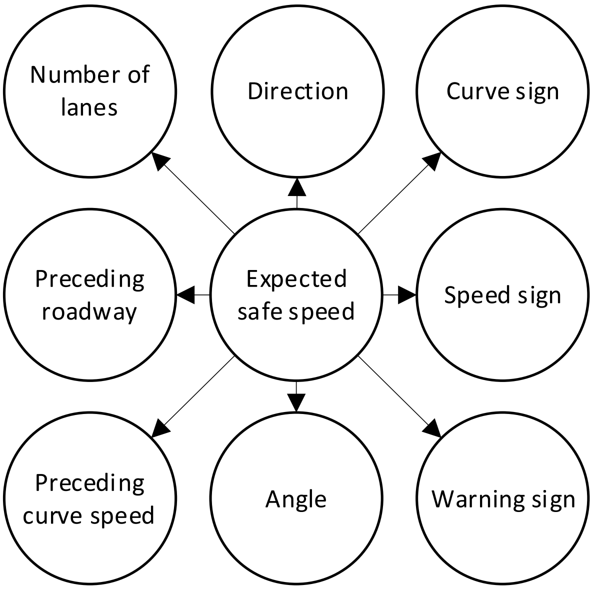


Figure 6-4 The naive Bayesian network (NBN).

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, Geiger, & Goldszmidt, 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.

6.3.3 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.

6.4 Results

The following sub-sections describe the results of the data analysis and modelling. Subsection 6.4.1 starts with the probability distributions of individual cues, subsection 6.4.2 models these cues into Bayesian Belief Networks (BBNs). These BBNs are tested and validated in section 6.4.3, and section 6.4.4 shows the use of a BBN in several case studies.

6.4.1 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 Figure 6-5 and can be interpreted as naïve *Prior* beliefs, so as independent variables.

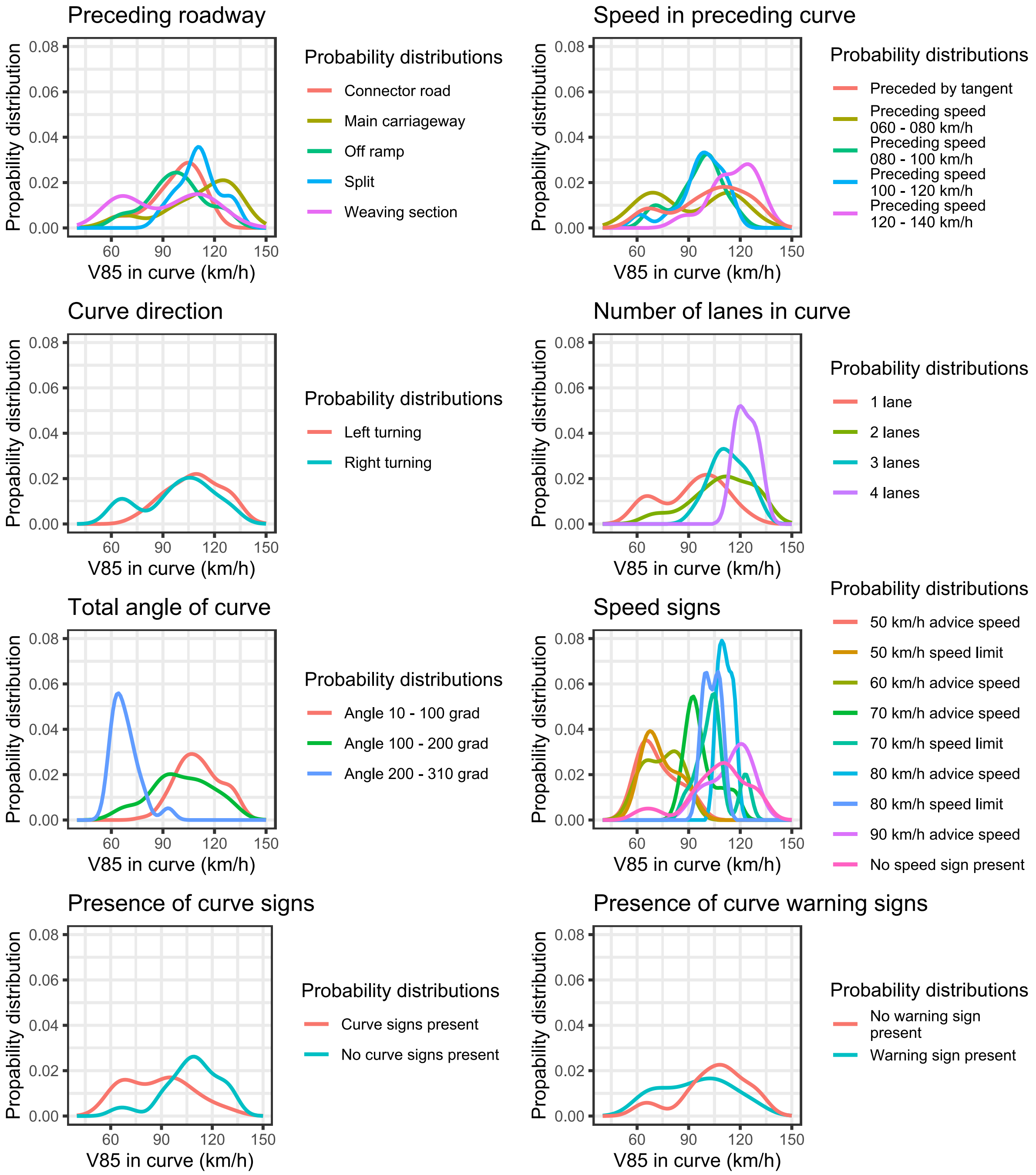


Figure 6-5 Probability distributions for the eight different variables (cues) related to the 85th percentile measured median speeds in a curve.

Figure 6-5 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).

6.4.2 Bayesian Belief Networks

The NBN in Figure 6-4 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 6-2. The average strength of influence in Table 6-2 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.

Table 6-2 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

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 Figure 6-6 and the average strength of influences per connection are given in Table 6-3.

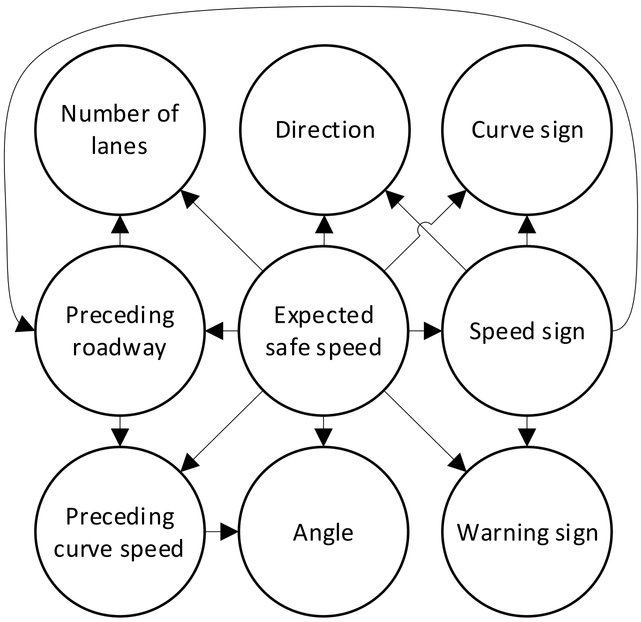


Figure 6-6 The tree augmented naive Bayesian network (TAN), learned from the data with the expected safe speed set as the class variable.

Table 6-3 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

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 E.

6.4.3 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 6-4, showing the variability around the correct predictions for most expected safe speeds is better predicted in the lower speeds than in the higher speeds.

Table 6-4 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							
		60 – 69	70 – 79	80 – 89	90 – 99	100 – 109	110 – 119	120 – 129	130 – 140
Measured 85th percentile median	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**

6.4.4 Case studies

The validation in the previous section was done using all observable evidence (cues) to predict an expected safe speed. 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 Figure 6-3. The temporal process of belief updating during curve approach is tested in two case studies. 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 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 Figure 6-7 without observed evidence, i.e. no visible cues.

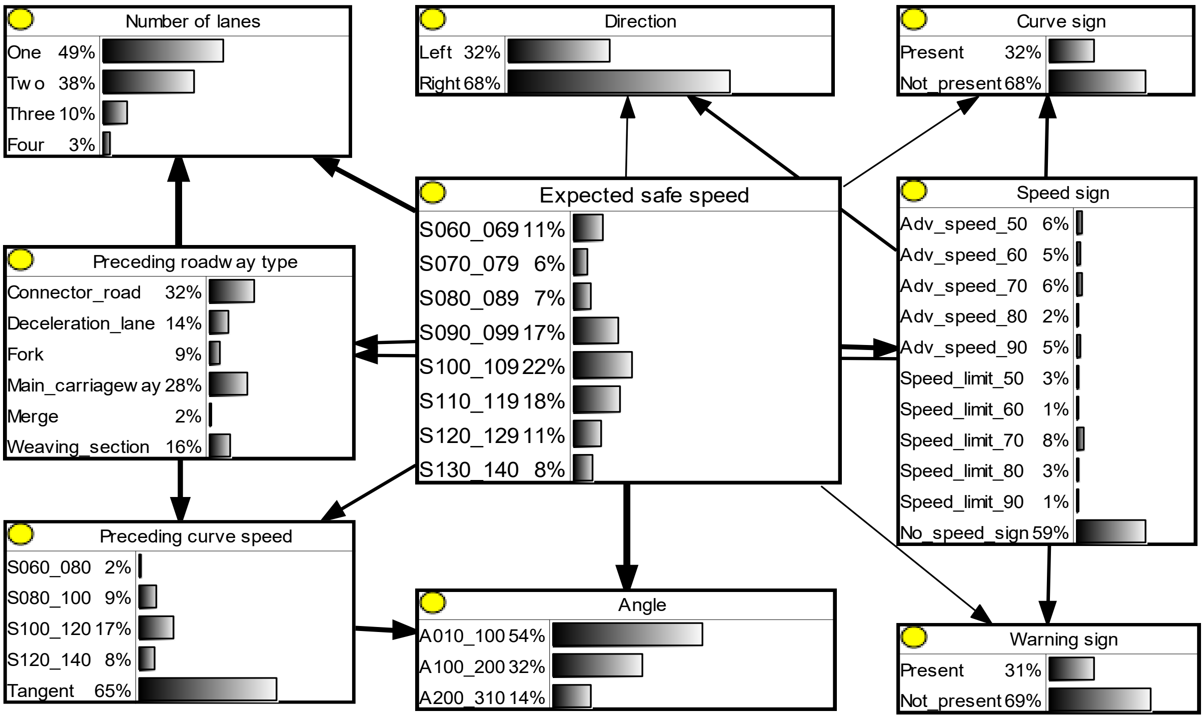


Figure 6-7 - The tree augmented naive Bayesian network with bar charts in each node showing the probabilities for each possible definition of that node, without having any evidence set. The thickness of each connection (arrow) indicates its strength of influence.

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 Figure 6-8 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 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.

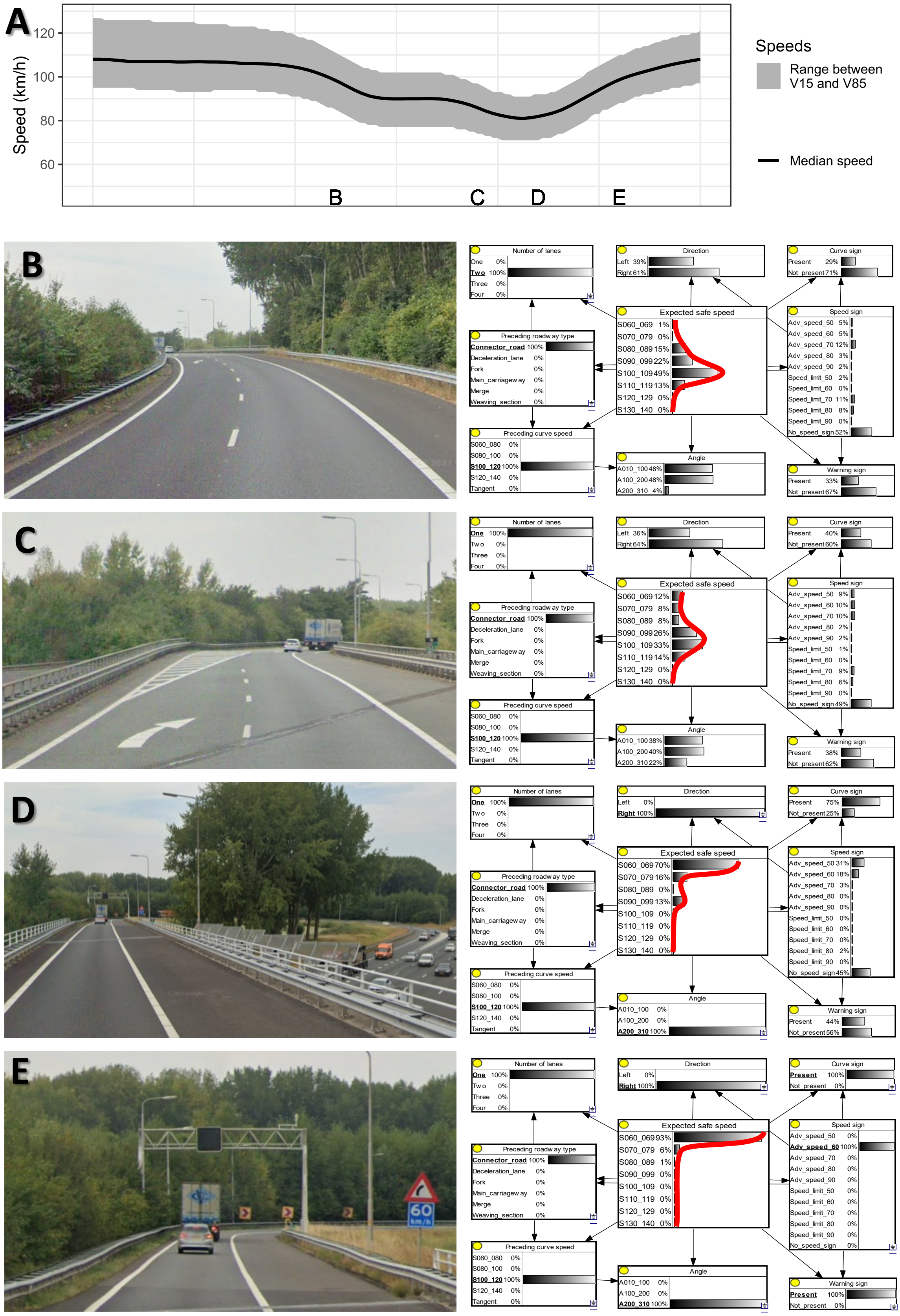


Figure 6-8 Case study 1 of belief updating upon curve approach. Panel A shows the measured operating speeds in this curve approach and the positions of the pictures. The pictures in panels B through E show the curve approach with the TAN next to it, updated with the visible cues and the resulting expected safe speed.

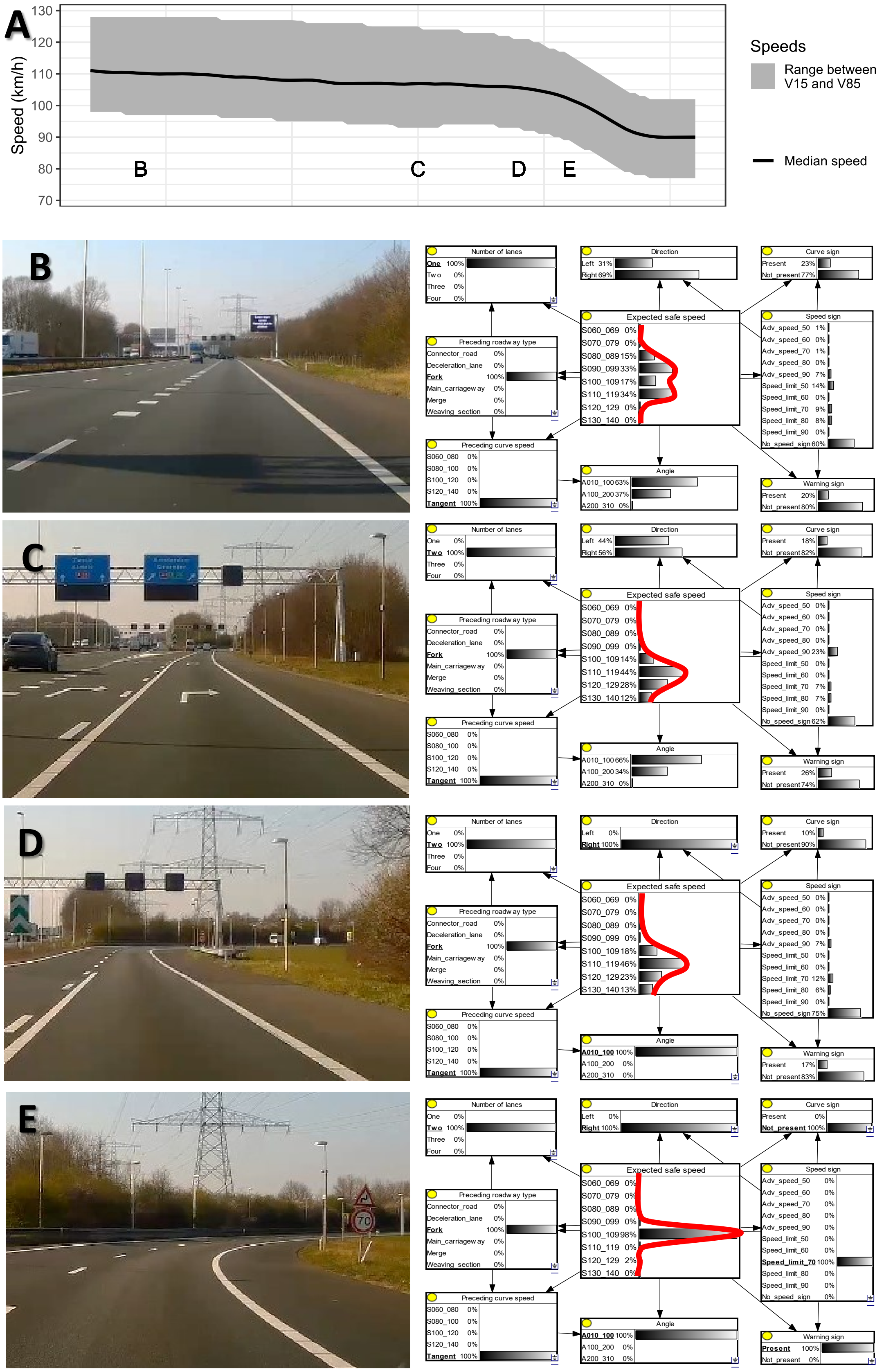


Figure 6-9 Case study 2 of belief updating upon curve approach. Panel A shows the measured operating speeds in this curve approach and the positions of the pictures. The pictures in panels B through E show the curve approach with the TAN next to it, updated with the visible cues and the resulting expected safe speed.

Several hypothetical cases were tested in the TAN. The results are given in Table 6-5 (and visually presented in Appendix F). Table 6-5 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 F shows the different variabilities of expected safe speeds visually as resulting probability distributions.

Table 6-5 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 F).

<table>
<tr><th># in appen-dix F</th><th>Preceding roadway type</th><th>Precedi ng 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>

6.5 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. 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, showing 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 might be skewed to one or two available records, and hence do not reflect the conditional probabilities of a cue. However, BBNs are known to perform well with missing data (Chen & Pollino, 2012). 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.

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 curve characteristics and driving speeds.

6.6 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, increasing accident risks because of speed differences among drivers or potential skidding. Dutch design guidelines can be updated using these insights and relate curve design to the cues the drivers are given in curve approach, making the design process more holistic and driver oriented. 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.

7 Discussion and Conclusions

The main aim of this dissertation was to *quantify the interaction between the drivers' behaviour and road characteristics during curve approach*, with the objective to apply these quantifications in freeway design. This interaction is assumed to be mainly governed by organised mental templates of expectations and behaviours which help the driver selecting the safe speed given certain curve characteristics in a mostly unaware process. These mental templates are known as (memory) schemata. This resulted in the following main research question:

What road characteristics trigger speed adjustments by drivers during curve approach?

Two main approaches were identified to answer this question: speed prediction modelling to quantify the relations between road characteristics and operating speed, and the human factors approach in order to quantify and understand drivers' cognitive processes of the interpretation of curve characteristics during curve approach to adjust their speed. This resulted in two research questions:

1. What road characteristics are correlated with speed behaviour during curve approach?
2. What road characteristics are utilized in drivers' information processing and speed adjustment decisions during curve approach?

This chapter discusses the results and draws conclusions in five sections.

In the first section, a comparison is made between the two main approaches: speed prediction modelling and the human factors approach. This comparison aims to address the two research questions. Each approach is first discussed separately, followed by a comparative analysis.

Next, in the second section, the main research question is addressed by discussing the relevant road characteristics identified in the different chapters. By categorising these characteristics into four overarching sets, the results from the various approaches are discussed.

Subsequently in the third section, several limitations inherent to this research are acknowledged and discussed. The fourth section discusses future research recommendations. Finally, the fifth section focusses on policy implications, particularly regarding the potential implementation of the findings of this dissertation in the Dutch road design guidelines.

7.1 Two approaches

In this section, the two research questions are discussed. To answer the first research question, speed prediction models were used which, in a behaviouristic approach, connect curve characteristics to speed behaviour to gain insights in the correlations between curve characteristics and operating speed. To answer the second research question, human factors approaches were used which adopt a cognitive perspective on how drivers interpret the curve characteristics and subsequently decide to decelerate based on those curve characteristics. These two approaches are visualised in the base conceptual model, shown in Figure 7-1 (which is identical to Figure 1-4, and repeated here for clarity). The connecting arrows, show that the speed prediction model uses *correlation* to correlate the curve characteristics with the operating speed (arrows indicated with 1) and that the human factors approach uses *causation* to reveal the relation between the physical reality and the human behaviour based on temporal relations (arrows indicated with 2).

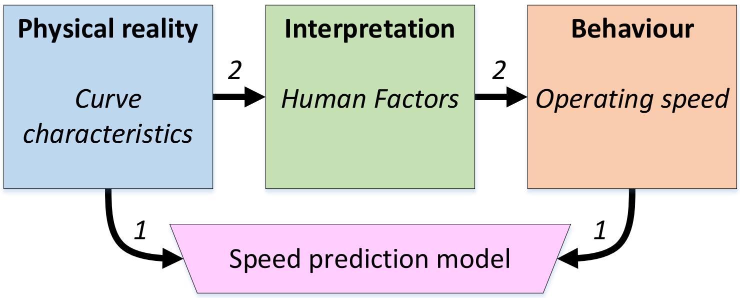


Figure 7-1 The base conceptual model in this dissertation. The connections show the corresponding research question

The next two sections will discuss the results from both approaches separately, followed by a comparison of the two approaches.

7.1.1 Speed prediction

Traditional speed prediction models have several deficiencies, including incorrect assumptions of constant operating speed in a curve, not considering the road (environment) upstream of the curve and biases in data collection, which result in unrealistic assumption of driver behaviour (Hassan, Sarhan, & Dimaiuta, 2011). Learning from these deficiencies in traditional speed prediction models, the research in this dissertation collected about one million free flow speed profiles from High Frequency Floating Car Data (HF FCD) in 99 locations, covering 153 curves. The extent of the spatial coverage of the speed profiles ensured that the majority of approaching elements could be included in the analysis, and to this end, all geometrical and environmental elements related to freeway design and layout were included in the dataset. Speed profiles benefit from the ability to probe speed data at any given position along the road design, instead of being bound to specific measurement sites. Furthermore, this approach ensured enough data to do proper statistical analysis.

The analysis of individual speed profiles and the development of parsimonious speed prediction models using 85th percentile speeds (chapters 3 and 4 respectively), helped to understand the correlations between curve characteristics and operating speeds. While traditional speed prediction models usually take the speed in the centre of a curve (Hashim et al., 2016; Hassan, Sarhan, Porter, et al., 2011), the analysis of the speed profiles in this dissertation took a dynamic approach in finding the position where drivers stop decelerating, which is in line with finding the minimum speed in a curve (Malaghan et al., 2020).

Especially when correlating the 85th percentile speeds to road geometry – which is quite common in speed prediction modelling (Llopis-Castelló et al., 2018; Russo, Biancardo, & Busiello, 2016) – prior research has consistently identified a substantial correlation between the horizontal curve radius and the operating speed in a curve. This research combined the radius and the number of lanes in a curve as predictors of the 85th percentile speeds, which resulted in an R^2 of 0.96. Based on individual speed profiles this resulted in an R^2 of 0.44. This difference in R^2 can be explained by introducing heterogeneity based on individual driver behaviour.

Next to the horizontal radius, the number of lanes and driver's approaching speed, the speed in a curve can further be explained by the deflection angle of the curve, the length of the curve, whether or not a discontinuity (deceleration lane, weaving section, etc.) was located in the curve, the direction of the curve, the width of the emergency lane and the presence of curve chevron signs. These are known elements that influence speeds in curves (Bobermin et al., 2021; Hassan, Sarhan, Porter, et al., 2011; Kazemzadehazad, Monajjem, Larue, & King, 2019).

The position where drivers start to decelerate was also investigated, since this is a measurable variable related to drivers taking action. Identifying this position and knowing which curve characteristics correlate with it, contributes to formulate a measurable memory schema: "start to decelerate". This is a new approach in speed prediction modelling, since most research focusses on speed in the curve, and the deceleration in front of curves (Hassan, Sarhan, Porter, et al., 2011; Malaghan et al., 2021) which gives no information about where drivers start reacting to a curve.

While analysing the 85th percentile speeds in relation to curve approach, it was observed that the point where drivers begin to decelerate was strongly correlated to the horizontal radius: sharper curves prompt earlier deceleration. However, when examining individual speed profiles, this correlation weakened, underscoring the variability in how drivers navigate curves. Incorporating individual speeds as an independent variable in regression analysis strengthened the correlation between road characteristics and driver behaviour. Similarly, factors like visibility, including sight distances and the visible angle of a curve, enhanced the correlation between individual speed profiles and curvature to a similar degree. While it is intuitive that increased visibility as a curve is approached leads to an increased correlation (more of it becomes visible), it is noteworthy that extended sight distances correspond to an earlier onset of deceleration. Additionally, the number of lanes and the absence of a discontinuity account for how much sooner drivers commence deceleration. Although sight distances are recognized for their influence on speeds along tangents (Hassan, Sarhan, Porter, et al., 2011), their impact on speed during curve approach has been underexplored. The research reported in this dissertation has addressed this gap.

7.1.2 Human factors

Human factors in this dissertation refer to the interaction between the driver and the infrastructure. Three conceptual approaches were used to analyse the human factors:

- analysis of the *cognitive processes* at play during curve approach;
- evaluation of *drivers' risk assessment* during curve approach;
- a comprehensive description of the *driving task*, covering the actions, behaviours and cognitive processes that a driver engages in while approaching a curve.

The next sections cover the findings based on these approaches, starting with the cognitive processes. This order stems from the understanding that the cognitive processes are considered the root for a driver's understanding of the infrastructure.

7.1.2.1 Cognitive processes

Cognition is described as *"the interpretation of sensed material"* by Wickens et al. (2021). The "sensed material" in this dissertation were the curve characteristics, sensed mainly by drivers' eyes. The interpretation of these curve characteristics is guided by schemata stored in long-term memory. The output of this process, which is fast and mainly unaware during curve approach, is an action (i.e., response selection and execution) which results in deceleration. It is however experimentally and conceptually challenging to understand how schemata are built (Walker et al., 2011). This is because schemata are constructs stored in memory and cannot be directly measured. Simply inferring correlation between the outside world and measured behaviour leads to generating speed prediction models (chapters 3 and 4). These models tend to have a large explaining power when using the horizontal radius of a curve. However, the horizontal radius of a curve is not a sensation which can be observed or interpreted by the driver. Instead, the driver observes the horizontal curve as either a kink or a hyperbola in the downstream alignment (Brummelaar, 1975; Wang & Easa, 2009).

To understand these cognitive processes, this dissertation employed several methodologies. Since curve driving is mostly a skill-based behaviour and hence relatively automatic and unaware, the survey in chapter 2 first made the participants aware of the process of speed adjustment for a curve using a comparison task between different pairs of curve pictures. Then, participants were asked which cues they used to adjust their speed. This revealed the driver's need for as much visibility of the curve trajectory as possible, in order to acquire the relevant information for their upcoming actions. Visible angle seems to be important in that matter, next to the number of lanes, signage and trees which were also mentioned as relevant aspects to speed adjustment. The importance of signage and number of lanes are in line with the findings of a previous study which used a questionnaire regarding curve speeds (Kanellaidis, 1995). Note however that Kanellaidis (1995) used closed questions, so the visible angle (or comparable variables) was not looked into in that study. The tendency of drivers to seek the greatest visible extent of a curve as possible has also been shown in eye-tracking research by Lappi (2014) and was discussed as the "future path model" for drivers' looking behaviour in a curve.

Next, in the on-road study (chapter 5), an eye tracking device measured the fixations of the drivers and these were compared to the output of their actions (i.e., deceleration). Furthermore, the on-road study used verbalisation to gain insight in the drivers thought processes about speed changes. The results from the eye tracking showed that drivers fixate on the Focus of Expansion (the point in the visual field where all perceived motion appears to converge, usually on the horizon) mostly before starting to decelerate, which is in line with the two point steering model, that shows that drivers fixate on the Focus of Expansion on tangents (Salvucci & Gray, 2004). Based on these results, it is hypothesised that drivers perceive the shift from a tangent into a curve in edges parallel to the curve like guardrails or treelines, which coincide with the Focus of Expansion, and use this visual cue to initiate deceleration. Only after the start of deceleration, drivers fixate on warning and speed signs and use this information to confirm a needed speed change. This contradicts common knowledge which state that speed or warning signs are the most important tools to aid the driver in speed adjustments for dangerous situations (Costa et al., 2022).

Finally, a Bayesian Belief Network (BBN) was developed in chapter 6, using insights from statistical learning on how prior probabilities resemble cognition (Griffiths & Tenenbaum, 2006). The BBN organises the complex relationships between curve characteristics and expectations of safe speed resembling schemata during curve approach. The Bayesian approach showed that multiple cues are used in the schemata during curve approach. Main cues drivers use during curve approach are the preceding roadway type (i.e., main carriageway or a type of discontinuity such as a weaving section), the number of lanes, the visibility of the curve in general, and the visible deflection angle in particular. The results, particularly those pertaining to the preceding roadway type and number of lanes, are in line with the Self Explaining Road concept, which postulates that the type of road should help the driver estimate the probability of certain properties of that road (Theeuwes & Godthelp, 1995). In this study these are curves that require the driver to decelerate. Speed and warning signs are much dependent on other variables, so they only complete – or underpin – schemata in that sense.

7.1.2.2 Individual risk assessments

Next to the general schemata identified, individual driving styles influence behaviour during curve approach. These driving styles are assumed to be mostly determined by the amount of risk the individual is willing to accept (Summala, 2007; Wilde, 1998). The analysis of individual speed profiles in this dissertation shows the correlation between individual speeds driven before a curve, the position where individuals start to decelerate and how fast they navigate a curve. Since higher speeds are associated with higher risks, these correlations could suggest that individual risk assessments during curve approach contribute to the variability in curve approach behaviour.

The survey and on-road study add some qualitative insights to individual speed behaviour. Nine percent of the survey respondents included reasons such as feeling hurried, status, excitement, fun and safety as motivations to select specific speed on a curve. These reasons were clustered in respondents' answers according to mentioned reasons regarding the type of vehicle, weather conditions and traffic conditions. These answers are in line with the verbalisations provided by the participants in the on-road study. About 23% of the verbalisations in the on-road study were driver related (i.e., not related to traffic or the road geometry or environment). This included 6% on driving style, 5% on comfort and various other reasons such as familiarity and interpretations of operating speed. Out of the verbalisations regarding decelerating for a curve, 10% included driver related verbalisations, of which 1% was on driving style and 5% was on comfort and the rest on other reasons such as familiarity, which is discussed below. This shows that comfort can be considered an aspect to accept a speed in a curve, and which differs per individual driver. These individual reasons were not further investigated in this dissertation. Van Winsum and Godthelp (1996) however showed that both the geometric elements and drivers safety margins have an effect on observed speed behaviour. So, each individual driver uses the same geometric elements as input, but makes a different trade-off towards a desired speed, because of different individual safety margins.

Familiarity with a curve was mentioned by 3% of the respondents in the survey, and in 6% of the overall verbalisations in the on-road study. Furthermore, familiarity was mentioned in 2% of the verbalisations related to decelerating for a curve. These percentages appear to be on the lower side, considering that other research has shown that familiarity significantly influences driving behaviour (Harms et al., 2021). Further, in the on-road study it was weakly related to higher driving speeds in curves and shorter fixation duration in look-ahead fixations in general and parallel edges specifically. Unfortunately, familiarity could not be investigated in the speed prediction modelling in chapters 3 and 4, because of privacy regulations.

7.1.2.3 Driving task

The task of approaching a curve, decelerating and driving through it is thought to be an operational driving task (Michon, 1985) and a skill based process (Ranney, 1994; Rasmussen, 1982). This means the curve driving task is highly automated and hence happens mostly unaware. And indeed, during the on-road study, the participants had difficulties verbalising their deceleration during curve approach, indicating unaware, automated tasks.

The descriptions of the driving task for curve driving (Campbell et al., 2012; McKnight & Adams, 1970) outline the actions a driver must take while approaching and navigating through a curve. These descriptions provide some helpful information, like the importance of recognizing the curve's angle. However, they do not explain the specific characteristics that are crucial for the driver during the approach to a curve. It is only mentioned that curves are identified and speed is estimated based on speed signs, without explaining which curve attributes are crucial for curve discovery and triggering safe speed expectations. Additionally, the existing driving task descriptions assume a long tangent approach to a curve.

Based on the findings from the human factor studies in this dissertation (chapters 2, 5 and 6), the driving task descriptions for the approach and curve discovery phases can be enhanced with the following insights:

Approach phase:

- Drivers form their expectations of safe speeds and adjust their driving speed based on the preceding roadway. Different types of roadways and their associated expectations have been identified:
    - Main carriageway: the driver assumes they can maintain their current speed. No specific cues are provided to signal the need for deceleration.
    - Discontinuity: markings (e.g. block markings and arrows) indicate the need for deceleration as the driver leaves the main carriageway, resulting in earlier deceleration. Different types of discontinuities can be distinguished:
        - Split: is associated with relatively high-speed expectations.
        - Deceleration lane: is associated with relatively low-speed expectations.
        - Weaving section: is associated with both high- and low-speed expectations.
- Drivers also form their expectations and adjust their driving speed based on the number of lanes preceding a curve. More lanes are linked with higher speed expectations, leading to higher speeds during curve approach and in the curve.

Discovery phase:

- Drivers identify an upcoming curve based on what they perceive at the Focus of Expansion. This is often seen as a kink in the alignment or trajectory of the road. Parallel edges, such as guardrails, treelines, or noise barriers, can assist drivers in spotting these curves at an early stage.
- If the trajectory of the curve itself is not visible, speed and warning signs may be the first indication of an upcoming curve:
    - Speed signs help the driver underpin the necessary speed adjustment during curve approach.
    - Warning signs help the driver understand why the speed limit is set.
    - Curve (chevron) signs aid in discovering the curve similarly to parallel edges, as they help visualize the curve's trajectory, offering better contrast and perspective.
- A safe speed is best estimated once the driver has a clear "overview" of the curve. Curves with higher visible angles are associated with lower safe speed expectations, resulting in earlier deceleration and lower speeds.

When the safe speed expectations do not align with the current operating speed, the driver starts to decelerate, or increases its deceleration. The interaction between drivers' behaviour and road characteristics is visualised in Figure 7-2, illustrating that different visual representations of curve characteristics generate different expectations.

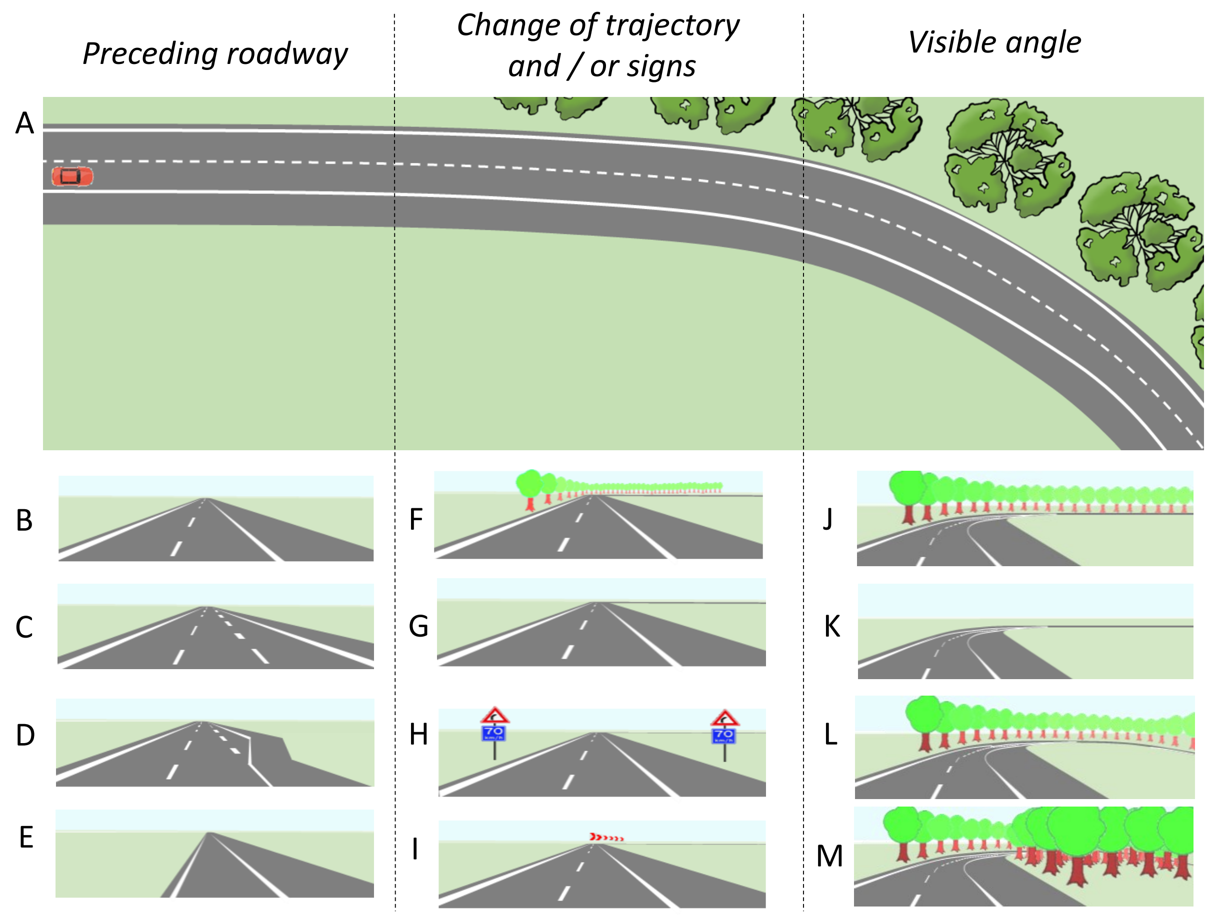


Figure 7-2 Visualisation of the road characteristics during curve approach. Panel A shows a top view of the curve approach. Panels B through E visualise several variations of preceding roadway from the drivers' perspective. Panels F though I show the change of trajectory and signs from the drivers' perspective. Panels J through M show the visible angle from the drivers' perspective in several settings (see text for further explanation).

Panel A offers a top-down view of a curve approach, featuring a two-lane carriageway and a right-hand curve with trees on the outer side. This scenario is further presented in sequential panels B, F, and J from the driver's perspective. Variations are displayed below these panels, with their implications explained here.

Panels B to E showcase various types of preceding roadways that would establish different expectations of safe speeds. Panel B illustrates a two-lane carriageway, generating expectations for relatively high safe speeds and hence no need to start decelerating. Panel C features a lane split, resulting in slightly lower safe speed expectations once the driver crosses the block markings. Panel D exhibits a deceleration lane, leading to even lower anticipated safe speeds upon entering and hence a need to start decelerating earlier. In contrast, Panel E displays a single-lane road, prompting significantly lower safe speed expectations compared to carriageways with two or more lanes.

Panels F to I highlight the identification of trajectory changes and thus the detection of a curve. Panel F underpins that the treeline on the outside of the curve clearly indicates a trajectory alteration. Panel G presents the same configuration but without the treeline, making the trajectory change less noticeable. When the trajectory change is challenging to observe, Panel H demonstrates that warning and speed signs can act as initial cues, while Panel I showcases that curve chevron signs aid in detecting a trajectory change.

Panels J to M demonstrate that the visible angle provides valuable information about required deceleration. Panel J features a visible angle of around 100 degrees, accentuated by the treeline. Panel K illustrates diminished detectability of the curve's angle due to the absence of the treeline. In Panel L, a curve with a visible angle of approximately 200 degrees implies a lower safe speed expectation than the curve in Panel J. Lastly, Panel M shows that obscuring the full deflection angle – achieved by obstructing the view with trees on the inside of the curve – leads to expectations of higher safe speeds than panel L. This might result in overestimating safe speeds which could result in accidents.

Note that the panel sequence in Figure 7-2 serves as an illustrative example. Real-world expectation-triggering and subsequent speed adjustments rely on the temporal order and visibility of specific curve characteristics during the curve approach.

7.1.3 Speed prediction versus human factors

The discussion above shows that speed prediction models only provide correlations, which do not imply causal relationships between curve characteristics and driver behaviour. This is most clearly seen in the important role the horizontal curve radius plays in the speed prediction models, while this curve characteristic is not perceivable by the driver. In other words, speed prediction models on their own cannot explain why a driver chooses a specific speed behaviour. Human factors research, on the other hand, helps to understand how the driver interprets the curve characteristics. By using human factors approaches in this dissertation, the schemata used by drivers approaching curves have been used to enhance the existing driving task descriptions, suggesting probable causal relations between several identified curve characteristics and drivers' behaviour. Bayesian statistics identified which cues are assumed to have the largest influence on the speed choice schemata.

The Bayesian Belief Network (BBN) developed in chapter 6 used the same variables as speed prediction models to measure driver expectations: curve characteristics and the operating speed. However, the constructed BBN acknowledged that the curve radius is not something a driver can directly perceive, and therefore it as not included as a variable in the model. Next to that, the probabilistic approach mimics the heuristics employed by drivers better than the deterministic approach (Rolls, 2011) employed in classic speed prediction models. In this way, constructing a BBN is speed prediction modelling that incorporates human factors knowledge.

Still, traditional speed prediction modelling equips freeway designers with valuable insights into how various design elements relate to speed, a crucial factor in the design process. This dissertation shows that operating speed inside the curve is mainly correlated to curve geometry, and thus relatable to lateral acceleration and comfort thresholds (Dhahir & Hassan, 2019a). Although the speed behaviour during curve *approach* is also correlated to the curve geometry, this is not as firm as the operating speed *in* the curve. Furthermore, the relationship between deceleration during curve approach and sight distances, along with the understanding that a curve's horizontal radius is not perceivable by the driver during curve approach (Brummelaar, 1975; Riemersma, 1988), highlights the importance of using a human factors approach. This approach helps determine which factors affect driver behaviour and should be included in speed modelling.

7.2 Road characteristics drivers use during curve approach

This section addresses the main research question using the insights gathered from the earlier chapters. This will be done through four subsections, each focusing on the findings related to significant road features uncovered in this dissertation's research. By examining these road features separately, it is aimed to uncover the specific curve characteristics that drivers take into account when approaching curves. These are assumed to be stored in their memory schemata related to deceleration during curve approach.

7.2.1 Horizontal curve alignment

Horizontal curve alignment consists of two main characteristics: horizontal radius and deflection angle. The research findings of this dissertation on these two characteristics are discussed in this sub section.

In chapter 2, it was found that 28% of survey respondents highlighted the horizontal radius as a reason for reducing speed, whereas only 4% mentioned the deflection angle itself. References to the horizontal radius tended to occur alongside comments about familiarity and the type of road. This indicates that participants draw on their past experiences to estimate the radius of the curve. On the other hand, the deflection angle was often linked to answers about superelevation and vertical alignment. This suggests a relationship between the deflection angle and the curve's visibility to the driver. Moreover, the *visible* angle emerged as a factor that might shed light on how participants evaluated the curve images. When the curves were arranged according to how frequently respondents selected them as the curve where they would drive the fastest, the visible angle was the only variable that mostly follows an ascending order in the list. Interestingly, the horizontal radius did not appear to serve as an explanatory variable.

In the speed prediction models (chapters 3 and 4) horizontal radius was the main explaining variable for speed behaviour. The starting point of deceleration was closer to the curve with larger radii, but with lower radii, larger variability was observed in the position where drivers start to decelerate. Speed in the curve is – especially with lower radii, up to 300 meters – very strongly correlated with the horizontal radius, showing lower speeds in tighter curves. The maximum amount of deceleration during curve approach was also moderately correlated with the horizontal radius; with tighter curves, drivers decelerate stronger. Deflection angle on the other hand was shown to have a weak negative correlation with the position where drivers start to decelerate and the speed in the curve. Again, there was a positive correlation between the *visible* angle at the point where drivers begin to decelerate and the variability of that specific point. The total deflection angle also positively influenced the variability in curve speeds. The parsimonious speed prediction models in chapter 4 did not take deflection angle into account, because it does not improve the models significantly.

During the on-road study (chapter 5), participants mentioned anticipating radius in 11% of the verbalisations for deceleration during curve approach while they do not explicitly mention deflection angle. Length of a curve – which is associated with this angle – was mentioned in about 1% of the verbalisations. Increased fixation duration into the curve after the start of deceleration indicates an increased interest in the trajectory of the curve and hence its length and deflection angle.

In the perspective analysis of curves in chapter 6 it was shown that the horizontal radius is hard to perceive by drivers, especially for sharper curves. By the time drivers visually detect the curvature of such sharp curves, they have already started the deceleration. The Bayesian Belief Network showed that other cues during curve approach help the driver in anticipating the safe speed and the correlated horizontal radius. The deflection angle of a curve emerged as a significant factor influencing drivers' expectations of a safe speed when approaching a curve. However, it is important to note that for this influence to occur, the deflection angle must be *visually* noticeable.

Horizontal radius plays a pivotal role in curve driving, both in terms of human and physical factors. It affects lateral acceleration (Reymond, Kemeny, Droulez, & Berthoz, 2001), impacting skid resistance and overall comfort, which are related to physical and human factors respectively. However, during curve approach other cues are used by the driver, because the radius itself is not recognisable from a driver perspective (Brummelaar, 1975; Fildes & Triggs, 1985). Notably, the *visible* deflection angle emerges as a key factor influencing a driver's expectations and speed adjustments when navigating a curve. This observation aligns with insights derived from perspective analysis of curves (Riemersma, 1988) while deflection angle has also been shown to positively correlate with accident risk (Shalkamy, Gargoum, & El-Basyouny, 2021).

7.2.2 Road configuration

The configuration of the road is primarily represented by the cross section and markings that drivers can easily recognise. This dissertation focuses on two distinctive road characteristics: the type of preceding roadway and the number of lanes.

Even though the curve images in the survey conducted in chapter 2 did not show any preceding roadways, 5% of the respondents still cited the type of carriageway as a factor influencing their chosen speed. When respondents mentioned the type of carriageway, it was frequently associated with references to radius and familiarity, suggesting a correlation between these factors. Over one-third of the respondents (35%) mentioned the number of lanes as a reason to drive faster through a curve. Furthermore, curve pictures with fewer lanes, tended to be picked as curves with lower preferred speeds by the respondents.

The analysis of individual speed profiles in chapter 3 showed that the presence of a discontinuity (i.e., weaving section, deceleration lane or split) and an increasing number of lanes relate to drivers starting to decelerate earlier. The number of lanes was the only variable next to the horizontal radius to be included in the parsimonious models (chapter 4) on speed development through curves. It was shown that two or more lanes resulted in about 4 to 8 km/h higher speeds during curve approach compared to approaches with a single lane. Furthermore, the models showed that operating speed before the curve was weakly correlated to the curvature and number of lanes alone. This means other variables are needed to explain the operating speed on the curve approach.

The road configuration consists of multiple components, which were not captured by how the fixations were labelled in the on-road study described in chapter 5. Instead, it can be assumed that the various components of the road configuration are all taken into account within the fixations on various Areas of Interest during both look-ahead fixations and guiding fixations. The road type was mentioned as a speed-related factor in a mere 1% of the verbalizations, while the number of lanes was referred to in less than 1% of the verbalizations during the experiment. This is much less than the 35% mentioned in the online survey, suggesting that drivers are not as actively aware of the number of lanes during driving than after a comparison task using curve pictures.

Using a Bayesian Belief Network to model expectations (chapter 6), revealed a strong influence of the preceding roadway on triggering expectations regarding a safe driving speed. The probability distributions showed that expectations for safe speed were higher on main carriageways, than on carriageways preceded by discontinuities. Furthermore, a strong influence was observed between preceding roadway and the number of lanes. Increasing numbers of lanes showed probability distributions with higher speeds and were related to discontinuities associated with higher speeds such as splits.

Although drivers find it hard to mention the effect of the preceding roadway, it is clear from this research that the design of the preceding roadway influences expectations and behaviour of the driver. This is in line with the Self Explaining Road approach, in which a type of road helps the driver in triggering the right expectations (Theeuwes & Godthelp, 1995). Furthermore, because drivers have the experience of driving faster trough curves with higher number of lanes, this is one of the key cues to trigger expectations regarding safe speed behaviour. This is in line with a study on the number of exit lanes performed by Calvi et al. (2018), who show lower speeds on a single exit lane.

7.2.3 Curve visibility

As discussed in paragraph 7.2.1 the visible part of a curve’s deflection angle influences expectations for a safe speed on a large scale. Two elements researched in this dissertation contributed to visibility: sight distances and parallel edges. Sight distances refer to a driver’s line of sight towards elements of the road environment. Parallel edges denote features like guardrails, treelines, or noise barriers that run alongside a curve’s alignment.

An overwhelming 71% of the respondents of the survey (chapter 2) mention visibility as a reason to drive faster through a curve. This is closely connected with the Dutch word "*overzicht*", loosely translated as overview, which was mentioned by 34% of the respondents. Even though traditional sight distances like road sight distance or sight distance on the trajectory of the curve do not show any relation with the ranking of curves by the participants, *visible* angle does. Edges or lines parallel to the curve mentioned include trees and guardrail, which were mentioned by 9% and 6% of the respondents respectively. These were clustered together in answers containing the term guidance, which was mentioned by 5% of the respondents. This suggests that these parallel edges create visual guidance for the driver.

Both road sight distance and stopping sight distance explained the variability of the position where drivers start to decelerate in the analysis of individual speed profiles (chapter 3), but these two sight distances were collinear. Maximum sight distance, which indicates the distance at which parallel edges such as guardrail, curve signs or noise barriers are visible, also contributed, albeit to a slightly lesser extent, to explaining the variability. The presence of these parallel edges did not correlate with any of the breakpoints in the analysis of individual speed profiles. Sight distances or parallel edges did not explain variability in the operating speeds inside the curve and were not part of the parsimonious speed prediction models in chapter 4.

In the on-road study outlined in chapter 5, a considerable portion of fixation duration was dedicated to guiding fixations. These fixations hold relevance for sight distances on the road, as they primarily assist drivers in maintaining their lane. Moreover, roughly 40% of the fixation duration was allocated to look-ahead fixations. This suggests that drivers frequently use sight distances extending beyond three seconds of driving time to plan their upcoming actions while driving. Although participants did not verbally mention any of the parallel edges, their gaze was drawn to them. Starting just before the moment participants initiated deceleration, fixation duration progressively increased, spanning from the Focus of Expansion to the far zone of a curve. As drivers navigated through the curve, their fixation on the parallel edges remained consistent, provided these edges are present.

The case studies employing the Bayesian Belief Network in chapter 6 showed that when cues become visually available during curve approach, drivers reacted to them in changing their speed, according to their expectations. Furthermore, the perspective analysis of curves showed that increasing the height of parallel edges increases the distance from which curvature is perceivable by the driver.

Overall, sight distances were correlated to the deceleration behaviour of drivers, because when cues with stored expectations become available, drivers adapt their speed accordingly. This is in line with the predictive processing framework (Engström et al., 2018), which shows that drivers adjust their behaviour – in a very broad sense – based on sensory input and it underpins schema theory (Plant & Stanton, 2013). Specifically, the presence of parallel edges increases the guidance of drivers, both during curve approach, and while driving in the curve itself. This is in line with Gestalt principles of bounding (Čičković, 2016; PIARC, 2016), which show that drivers heuristically assume that these edges are parallel to a curve and therefore can be used to infer the curve's trajectory.

7.2.4 Road signs

This dissertation has also explored the impact of road signs pertaining to curves: curve signs (chevrons), speed signs, and warning signs.

Curve signs in this dissertation refer specifically to chevron signs which are placed in the curve. These signs are mentioned by 20% of the survey respondents in chapter 2 to be of influence on their speed selection. These answers are clustered together with answers on the number of lanes. When ranking the curve pictures by how many times a curve was picked as the fastest by the respondents, pictures with curve signs were in the lower part of the ranking. The curve pictures did not show any speed or warning signs, nor did any of the respondents mention speed or warning signs as a cue for their operating speed.

The visibility of curve signs at the moment drivers started to decelerate, explains the variability of that position in the analysis of individual speed profiles (chapter 3). It explains the relation between visible curve signs and a later moment of deceleration. Furthermore, the presence of curve signs was related to higher speeds in a curve. Although the speed indicated on speed signs was seen to correlate with the speeds taken to drive through curves, it did not account for the diversity in speeds observed in the regression analysis. The parsimonious speed prediction models (chapter 4) did not include the presence of any road signs.

During the on-road study described in chapter 5, participants referred to curve signs in 0.2% of their verbalisations, warning signs in 0.7%, and speed signs in 8.4%. Additionally, participants mentioned in 4.5% of the verbalisations that they were driving faster than the speed sign indicated and in only 0.2% they mentioned they were driving slower than allowed. When participants mentioned they decelerated for a curve, 13.2% of them also mentioned a speed sign, which was the most common co-occurrence with deceleration. The second-highest of co-occurrences, at 12.0%, was when participants mentioned discovering the curve together with mentioning decelerating. In addition, participants revealed they used the speed signs as a confirmation or speed indication after curve discovery. This is in line with the fixation measurements; only after the participants slow down, they start fixating on road signs in general, unless the speed sign itself is the first cue drivers see. Fixation distribution on curve signs is relatively higher in curves that did not have clear parallel edges, suggesting that a row of curve signs can serve as a substitute for a clear parallel edge.

When modelling the cues which influence driver expectations using a Bayesian Belief Network (chapter 6), it became clear that curve and warning signs have a relatively minor influence on drivers' speed expectations. Probability distributions showed that the presence of curve signs just tells a driver to decelerate, but not how much. There was however a moderate dependency between speed and warning signs. Speed signs showed narrow probability distributions for the operational speeds, based on the speed indicated on the sign. This narrow probability distribution suggests high influence of the indicated speed on speed signs on the expectation building for drivers during curve approach about their safe speed. And indeed, when modelling the expectations in a Bayesian Belief Network, using dependency upon other characteristics, speed signs still had a moderate influence on expectations. In the case studies the speed signs mainly act as a confirmation about the safe speed, i.e. narrowing the probability distribution of the expected safe speed.

Generally speaking, curve signs can help drivers' judgment on curvature, especially when parallel edges are absent. However, aiding the driver in judging the sharpness of the curve could potentially lead to higher speeds. In a simulator study by Calvi, D'Amico, Bianchini Ciampoli, and Ferrante (2019), the application of curve signs (chevrons) was shown to help the drivers understand the sharpness of a curve better. In this way, placing curve signs can substitute the absence of parallel edges. Warning signs alone do not contribute significantly to drivers' ability to anticipate the need for deceleration before a curve. It is in the combination with speed signs that drivers trigger expectations about safe speeds. This is in line with a study by Charlton (2007), which demonstrates that warning signs become more effective when they are combined with other road treatments. Generally, when speed signs are present, they tend to align with the demands imposed by the curve's horizontal radius, although they typically display slightly lower speeds than what drivers actually drive. The speed signs drivers observe appear to contribute to strengthening their expectations about the necessary deceleration before approaching a curve. While there is still a common belief within the research community regarding the substantial impact of speed signs on speed adjustments (Costa et al., 2022), it is recognized that drivers primarily rely on cues from the road itself, and using speed signs as supplementary information (Shinar, 2017d). Nonetheless, road signs in general prove to be particularly valuable during reduced visibility conditions.

7.3 Limitations

The main chapters in this dissertation build on each other. Several knowledge gaps which remained in a single chapter, were then taken up in a following chapter. So, not all limitations mentioned in single chapters are limitations of this dissertation as a whole. However, some overarching limitations remain, which are discussed in the next three sub-sections.

7.3.1 Sample selection

Only curves in main carriageways and connector roads in interchanges were researched in this dissertation. Other schemata and speed behaviour may be present in curves in on and off ramps due to the need to slow down towards an intersection or to speed up from one.

Next, the speed data gathered for the analysis of the speed profiles, for the generation of speed prediction models and for building the Bayesian Belief Network were obtained from a faster sub-group than the entire driving population: users of the navigation and speed trap warning app "Flitsmeister". It has been shown in paragraph 3.2.4 that these app-users drive on average 5 km/h faster than the average driver based on measurements from loop detectors, but that is all we know of this group. No further insights into the driver demographics or driving history are known, nor about the type of vehicles used, so no study of personal characteristics and an understanding of their impact on schemata was performed.

Furthermore, the samples in the survey and on-road study were skewed to (young) males. The survey results show that (young) males differ in mentioning specific characteristics that are relevant for speed selection (e.g. superelevation, vertical alignment, guidance and overview) compared to the entire sample, as explained in paragraph 2.3.4.

7.3.2 Data gathering

In this dissertation, the survey in chapter 2 only used static images, while locomotion is known to provide information about speed (Wolfe et al., 2022). Since discussing speed based on static images is not the same as choosing a speed while moving (Charlton & Starkey, 2017b), the results from the survey can only be used exploratively. The verbalisation in the on-road study was difficult for the participants and the on-road study had a relatively low number of participants, which could have resulted in biased results. Furthermore, the quantitative data gathered on eye fixations, includes Area's of Interest located up to 300 meters beyond the position of the eye tracker, making it hard to distinguish the correct AoI in the complex road environments used in the on-road study.

Generally, the conclusions drawn in this dissertation about the schemata drivers have on curve approach are *assumptions* derived from the gathered data. The data contains only measurable and quantifiable variables, such as operational speed, curve characteristics, fixations and verbalised or transcribed thoughts. The latter comes closest to actual schemata, but schemata themselves are not directly measurable (Walker et al., 2011), and are therefore conceptually still open for discussion (Plant & Stanton, 2013), since surveys and verbalisations can be biased. The concept of a mental representation of expectations about safe speeds in curves, connected to curve characteristics is however shown to have explanatory power related to actual operational speeds as shown in the case studies in chapter 6.

7.3.3 Generalisation

Since all data was gathered in The Netherlands, applying the insights in road and curve design to other countries should be done with caution and consideration of local design characteristics and driving culture. For the conclusions drawn on drivers' expectations, it is clear that, even in neighbouring countries, drivers build different schemata based on how local design dictates curve approaches. Specifically, the use of steeper grades in the vertical alignment and poor road maintenance conditions – both were absent in the studied curves in this dissertation – might have influences on driver expectations.

7.4 Recommendations for future research

The methodological advancements and innovative approaches in this dissertation contribute to expanding knowledge in the field of traffic psychology, shedding light on the cognitive processes underlying driver behaviour and paving the way for further investigations.

In this dissertation, the research focused on several important aspects related to driver behaviour during curve approach. Firstly, it identified the position at which drivers begin to decelerate and examined how curve characteristics influence this deceleration point. Additionally, the study explored the cognitive processes underlying drivers’ speed adjustments in relation to these curve characteristics.

By expanding our knowledge of driver behaviour during curve approach and exploring the impact of different variables, this research contributes to the development of more effective road safety measures (e.g. expectations) and advancements in automated vehicle technology because speed behaviour is quantified (Markkula et al., 2023). The provided knowledge on human driver behaviour during curve approach in this dissertation can also be regarded as a reference for testing automated vehicles. In this way automated vehicles will mimic human driver behaviour instead of adhering to inferred speed behaviour from curve radius alone. This results in a more homogeneous traffic flow, by excluding automated behaviour, which is assumed to be more safe (Aarts & Van Schagen, 2006).

The on-road study (chapter 5) revealed that drivers fixate on parallel edges to the curve. Additionally, it was observed that increased sight distance on curve trajectory (inferred by parallel edges in the analysis of individual speed profiles, and related to the visible deflection angle) led to earlier deceleration. Still, the perspective analysis in chapter 6 only assumed an effect of the height of these parallel edges on the visibility and speed behaviour based on the driver’s perspective on a curve (Brummelaar, 1975; Fildes & Triggs, 1985). An experiment in a controlled environment, with only the height or visibility of parallel edges changing, could give better – and quantifiable – insights into the effect of the height of parallel edges on speed behaviour during curve approach. The same is true for the positioning of speed and warning signs when the trajectory of a curve is not visible (enough) from a distance. In general, the real-world observations in this dissertation, can be studied independently in a controlled environment (e.g., advanced driving simulator, experiments on a (race) test track or an (online) experiment using different video’s to test the influence of specific road characteristics on expectations) to gain more in depth knowledge about speed behaviour (Lappi, 2022).

In this dissertation only curves on main carriageways and connector roads in intersections were researched. To fully understand curve-related schemata on freeways, it is needed to conduct research that explores how drivers build their schemata for curves in both on and off ramps (slip roads). This would complement the analysis presented in this dissertation. A way forward could be to develop a database containing all connector roads, on and off ramps in The Netherlands, combined with the relevant curve characteristics mentioned in this dissertation. This database could be used to further develop the Bayesian Belief Network presented in chapter 6.

Individual reasons to decelerate (driving style) were not further investigated in this dissertation. This requires further research, especially since it is known that various types of road users such as car drivers and motorcyclists, interpret the same environment differently (Walker et al., 2011), or have distinct perspectives of the road due to varying heights, e.g. truck drivers.

Finally, only interactions between the driver and the road were researched in this dissertation. The interactions between the vehicle and the road – i.e., skid resistance – were not researched, but determine the safe outcome of a speed choice made by the driver. This calls for research into skid resistance, based on driver's speed choices to understand which physical forces are required in different situations. The information regarding deceleration at the beginning of a curve, as presented in the speed prediction models, or the diverse speed expectations outlined in chapter 6, can serve as valuable starting points for guiding further research in this area.

7.5 Applying human factors knowledge in road design

It is hoped that with this dissertation awareness is raised in the road design community that speed behaviour during curve approach is not only dependent on the curve geometry itself. Factors such as preceding road elements, sight distances, warning and speed signs and continuous elements placed parallel to the curve have significant influences. Therefore, horizontal curve design should always consider the surrounding driving context. The driving task (presented in paragraph 7.1.2) and the individual effects of design elements (presented in paragraph 7.2) can help analyse existing designs or accident hot spots by answering two questions:

- What speed behaviour is to be expected in this location?
- What do drivers expect to happen? And is this in line with the physical reality?

However, to be pro-active in road safety, knowledge of the driver's perspective of our road designs needs to be implemented in the design phase (SWOV, 2018; Wegman, 2017). This calls for design guidelines which have a holistic approach, considering curves in the entire road environment, i.e., considering preceding elements and surroundings. The following sections use the insights from this dissertation to generate design guidelines for future freeway curves.

Since design guidelines should be easily interpretable and applicable by road designers, the findings and knowledge acquired in this dissertation have been summarized into a table that outlines permissible combinations of design elements. This table also shows which combinations to avoid. The main design characteristic of curves is the horizontal radius (Rijkswaterstaat, 2022). So, to keep that consistent from a designer's point of view, intervals of radii have been grouped. To do so, equation 7-1 is used – which was developed in chapter 4 as part of the parsimonious speed prediction models – because this connects the horizontal radius (R_h) and the 85th percentile speed in the curve ($V85_{BP2}$). Trying to take a driver perspective here, the inverse of equation 7-1 (leaving out the binary variable *nLanes1* resembling number of lanes being one or more than one), gives an equation which can be used to calculate the horizontal radius (R_h) based on an 85th percentile speed ($V85$). This is presented as equation 7-2:

$$V85_{BP2} = 28 * \ln(R_h) + 7 * nLanes1 - 58 \quad [7\text{-}1]$$

$$R_h = e^{\frac{v85+58}{28}} \quad [7\text{-}2]$$

Equation 7-2 can then be used to create intervals of horizontal radii spanning a range of 10 km/h, which is a fair threshold for design consistency (Lamm et al., 1988). The lowest radius available in this dissertation is 60 meters, which corresponds to a *V85* of 57 km/h. The following cut offs for the intervals are presented in Table 7-1. Rounding the calculated radii to values of 5 meters, provide usable intervals presented in Table 7-2 and Table 7-3.

Next, the preceding roadway, number of lanes and deflection angle are used as design elements to differentiate the holistic environments. These elements have impact on both speed behaviour and expectations and are easily distinguishable during the design process. Using the insights from the Bayesian Belief Network (BBN) which mimics driver expectations (chapter 6), Table 7-2 and Table

7-3 are filled to reflect whether or not specific combinations are within or outside drivers' expectations. To do this, the Tree Augmented Naïve Bayes Network is used primarily, and the individual probability distributions are used to better reflect specific combinations which were not available in the dataset. This means, when a specific variable suggests that no safe speeds are to be expected in a certain range, this is shown in the tables (e.g., the amount of 4 lanes indicates that radii lower than 520 m. are not to be expected and hence labelled red). Specifically for main carriageways the permissible combinations were limited further than the BBN suggests, to reflect basic criteria for freeways: continuous high speeds and the possibility to overtake (i.e., at least two lanes and no curve radii < 740 m).

Table 7-1 The relation between the 85th percentile speeds in curves (*V85*) at 10 km/h intervals, the horizontal radius (*R_h*) and the position of the start of deceleration in front of the curve (*BP1*).

V85	*R_h*	*BP1*
57 km/h	60 m	430 m
67 km/h	87 m	375 m
77 km/h	124 m	320 m
87 km/h	177 m	264 m
97 km/h	253 m	209 m
107 km/h	362 m	154 m
117 km/h	518 m	98 m
127 km/h	740 m	43 m

Since the *visibility* of the deflection angle was shown to have a major impact on how drivers anticipate the curve, this is included as a control variable. If the entire deflection angle is not visible from the moment drivers start their comfortable deceleration, additional measures are to be taken. This distance is taken from the developed parsimonious speed prediction models, equation 7-3, which determines the position of breakpoint 1 ($pos50_{BP1}$) as the position where drivers start to decelerate as an function of the horizontal radius (R_h):

$$pos50_{BP1} = 155 * \ln(R_h) - 1067 \quad [7\text{-}3]$$

The results of using equation 7-3 are presented in Table 7-1 in line with the chosen intervals, and the averages of the results for two interval edges are presented in Table 7-2 and Table 7-3 as a controlling variable for sight distances. If the deflection angle is not fully perceivable from this position in front of the curve, designers could suggest clearing out sight obstructions such as bushes, increasing the height of parallel edges or applying curve signs (chevrons). If these measures are not possible, speed and warning signs need to be installed to inform the drivers to slow down, as the road environment itself is not able to tell the driver to do so.

This approach leads to Table 7-2 and Table 7-3, which are shown on the next two pages.

Table 7-2 Permissible combinations – shown in green – of design elements on main carriageways and on connector roads. Controlling for visible angle and driver expectations.

Preceding roadway	**Number of lanes in curve**	**Range of deflection angles**	**Range of horizontal radii (m)**							
			60 - 85	85 - 125	125 - 175	175 - 255	255 - 360	360 - 520	520 - 740	> 740
Main carriageway	1	10 - 100								
		100 - 200								
		200 - 300								
	2	10 - 100								
		100 - 200								
		200 - 300								
	3	10 - 100								
		100 - 200								
		200 - 300								
	> 3	10 - 100								
		100 - 200								
		200 - 300								
Connector road (not the first curve)	1	10 - 100								
		100 - 200								
		200 - 300								
	2	10 - 100								
		100 - 200								
		200 - 300								
	3	10 - 100								
		100 - 200								
		200 - 300								
	> 3	10 - 100								
		100 - 200								
		200 - 300								
Extra warning and speed signs necessary if combination is labelled orange and / or **deflection angle is not visible** from the amount of meters in front of a curve stated here			400	350	290	235	180	125	70	20

Table 7-3 Permissible combinations – shown in green – of design elements following splits, weaving sections and deceleration lanes. Controlling for visible angle and driver expectations.

Preceding roadway	Number of lanes in curve	Range of deflection angles	Range of horizontal radii (m)							
			60 - 85	85 - 125	125 - 175	175 - 255	255 - 360	360 - 520	520 - 740	> 740
Fork	1	10 - 100								
		100 - 200								
		200 - 300								
	2	10 - 100								
		100 - 200								
		200 - 300								
	3	10 - 100								
		100 - 200								
		200 - 300								
	> 3	10 - 100								
		100 - 200								
		200 - 300								
Weaving section	1	10 - 100								
		100 - 200								
		200 - 300								
	2	10 - 100								
		100 - 200								
		200 - 300								
	3	10 - 100								
		100 - 200								
		200 - 300								
	> 3	10 - 100								
		100 - 200								
		200 - 300								
Deceleration lane	1	10 - 100								
		100 - 200								
		200 - 300								
	2	10 - 100								
		100 - 200								
		200 - 300								
	3	10 - 100								
		100 - 200								
		200 - 300								
	> 3	10 - 100								
		100 - 200								
		200 - 300								
Extra warning and speed signs necessary if combination is labelled orange and / or **deflection angle is not visible** from the amount of meters in front of a curve stated here			400	350	290	235	180	125	70	20

A Sensitivity Analysis on Thresholds for Breakpoint Definition in the Analysis of Individual Speed Profiles

The position of breakpoint 1 and 2 are defined based on the acceleration profile. The first position in front of the curve start where the acceleration equals 0 m/s² is defined as breakpoint 1. The first position after the curve start where the acceleration equals 0 m/s² is defined as breakpoint 2. Since the measurements are smoothed and taken at a 1 second interval, it is improbable that a measurement will exactly hit 0 m/s². So, thresholds need to be set in order to find the positions of most breakpoints in the acceleration profiles. Thresholds can be set in a range of acceleration above and below 0 m/s², and in the number of seconds (measurements) the acceleration profile should be within that range. Figure A-1 shows the theoretical impact of setting these different thresholds.

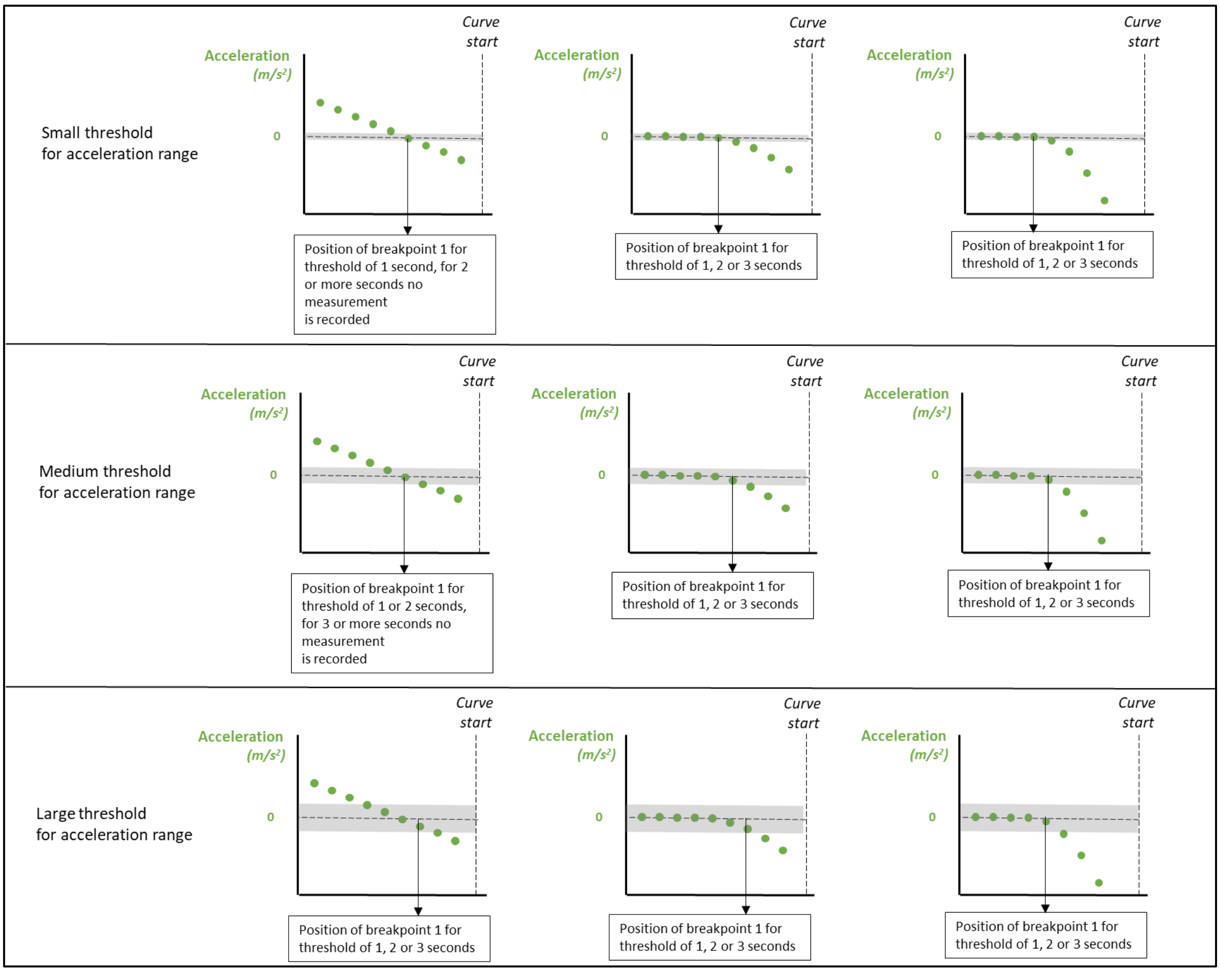


Figure A-1 Effects of different thresholds on the position of breakpoint 1 in three different scenarios. The scenario's show individual acceleration measurement points. For three acceleration thresholds (small, medium and large) the bandwidth is shown in grey. How much points (measurements per second) fall within the bandwidth, defines if a breakpoint is defined based on the threshold set for the amount of seconds an acceleration profile remains in the set bandwidth. It shows that based on the different thresholds, the position of the breakpoint may shift, or may not even be recorded.

In order to test the effect of the different thresholds, five random curves were selected to test different sets of thresholds. Of each curve the median speed and acceleration profile were plotted (thick line, respectively in red and green). Interquartile ranges of both speed and acceleration are plotted in thin lines.

The next definitions of thresholds are tested in the profiles:

1. Minimum and maximum acceleration needs to be:
    a. Between -0.05 and 0.05 m/s^2
    b. Between -0.1 and 0.1 m/s^2
    c. Between -0.2 and 0.2 m/s^2
    d. Between -0.3 and 0.3 m/s^2
2. Duration in which the acceleration profile needs to be within the threshold of minimum and maximum acceleration
    a. 1 second
    b. 2 seconds
    c. 3 seconds

For each of the 12 different sets of definitions a bar plot is shown for the positions of the breakpoints 1 and 2, and the amount of recorded breakpoints is shown.

Below, the five results are shown and captioned with a analysis on the effects of the thresholds.

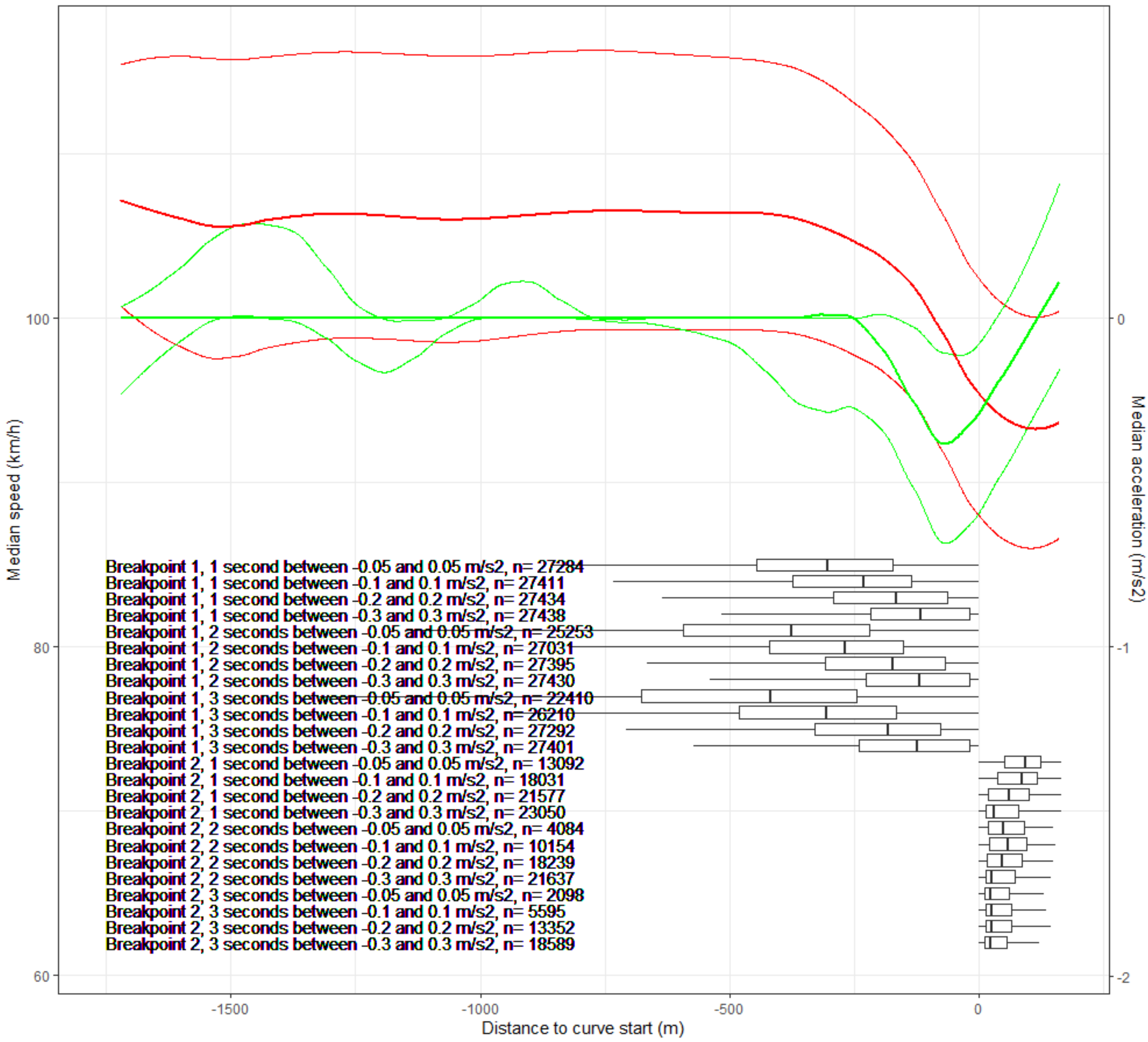


Figure A-2 Summarised speed and acceleration profile based on 27440 unique profiles for a curve with a radius of 250 m and 2 lanes. Based on the median acceleration profile, breakpoint 1 should be positioned around 250 m in front of curve start. A threshold of 1 second between -0.1 and 0.1 m/s^2 approaches this the best with the most amount of recorded breakpoints. Breakpoint 2 should be positioned around 120 m after curve start. A threshold of 1 second between -0.1 and 0.1 m/s^2 approaches this the best with the most amount of recorded breakpoints. A threshold of 1 second between -0.05 and 0.05 m/s^2 approaches this the best, but loses a lot of recordings. Enlarging the threshold to a range between -0.1 and 0.1 m/s^2 with the keeps the median position about the same, but adds much more recordings.

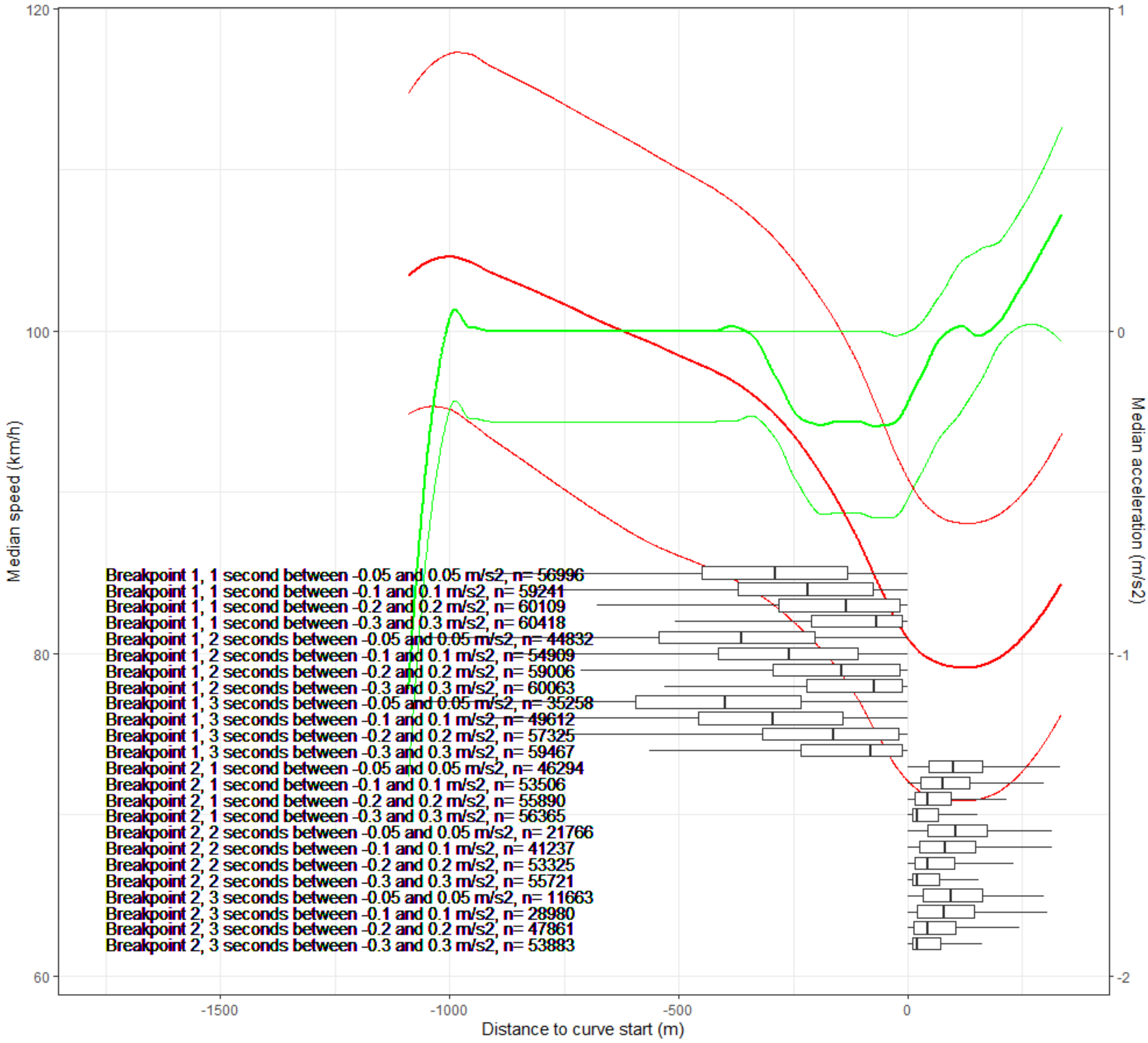


Figure A-3 Summarised speed and acceleration profile based on 60605 unique profiles for a curve with a radius of 255 m and 1 lane. Based on the median acceleration profile, breakpoint 1 should be positioned around 350 m in front of curve start. A threshold of 2 second between -0.05 and 0.05 m/s^2 approaches this the best but loses a lot of recordings. Decreasing the threshold 1 second with the keeps the median position about the same, but adds much more recordings. Breakpoint 2 should be positioned around 75 m after curve start. A threshold of 1 second between -0.1 and 0.1 m/s^2 approaches this the best with the most amount of recorded breakpoints.

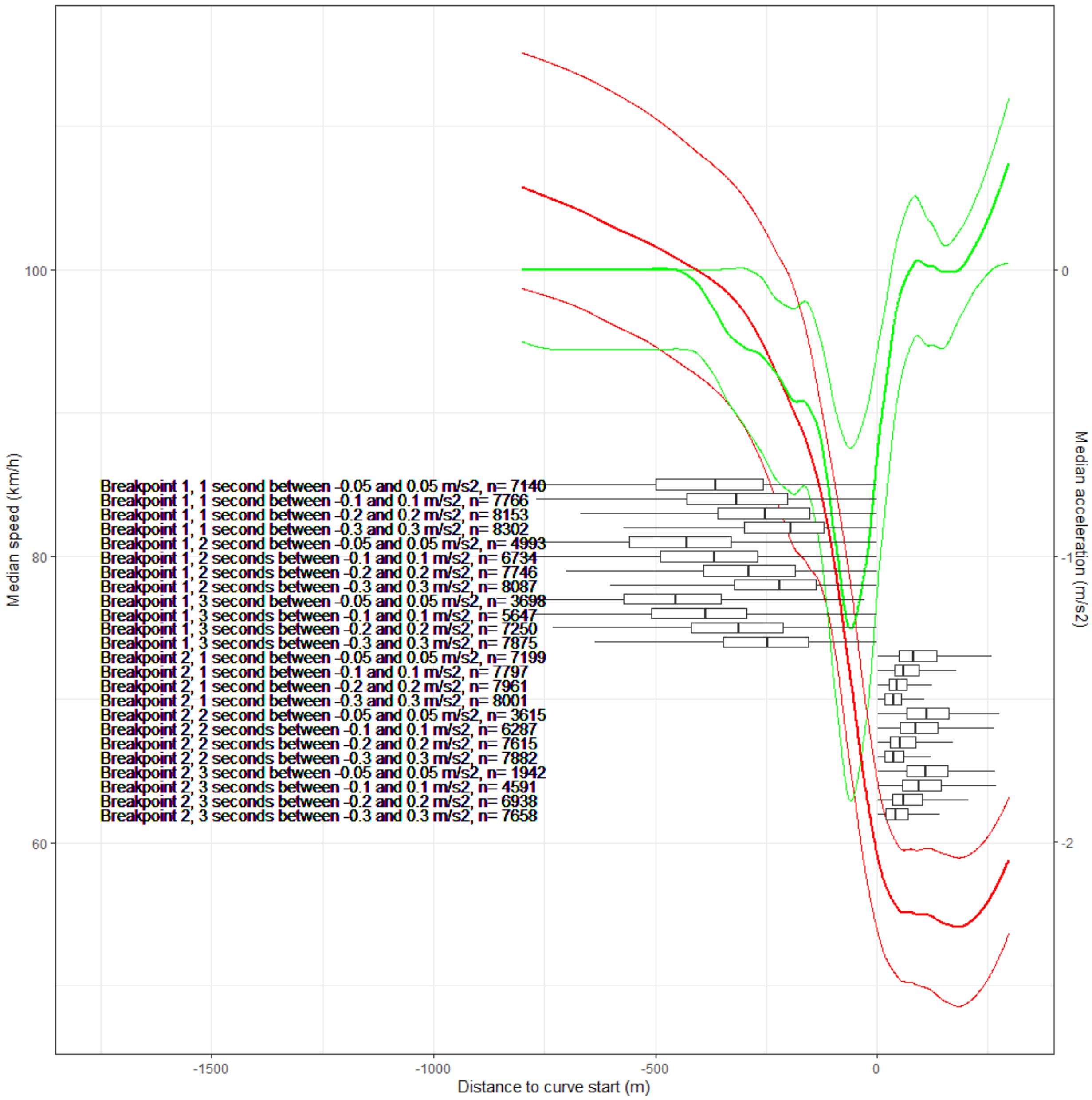


Figure A-4 Summarised speed and acceleration profile based on 8685 unique profiles for a curve with a radius of 75 m and 1 lane. Based on the median acceleration profile, breakpoint 1 should be positioned around 450 m in front of curve start. A threshold of 3 second between -0.05 and 0.05 m/s^2 approaches this the best but loses a lot of recordings. It also does not match up with the kink in the median speed profile, which is located around 350 m in front fo curve start. A threshold of 1 second between -0.1 and 0.1 m/s^2 approaches this the best with the most amount of recorded breakpoints. Breakpoint 2 should be positioned around 75 m after curve start. A threshold of 2 second between -0.1 and 0.1 m/s^2 approaches this the best but loses a lot of recordings. Decreasing the threshold to 1 second, increases the amount of recordings significantly, and lines up with the kink in the median speed profile.

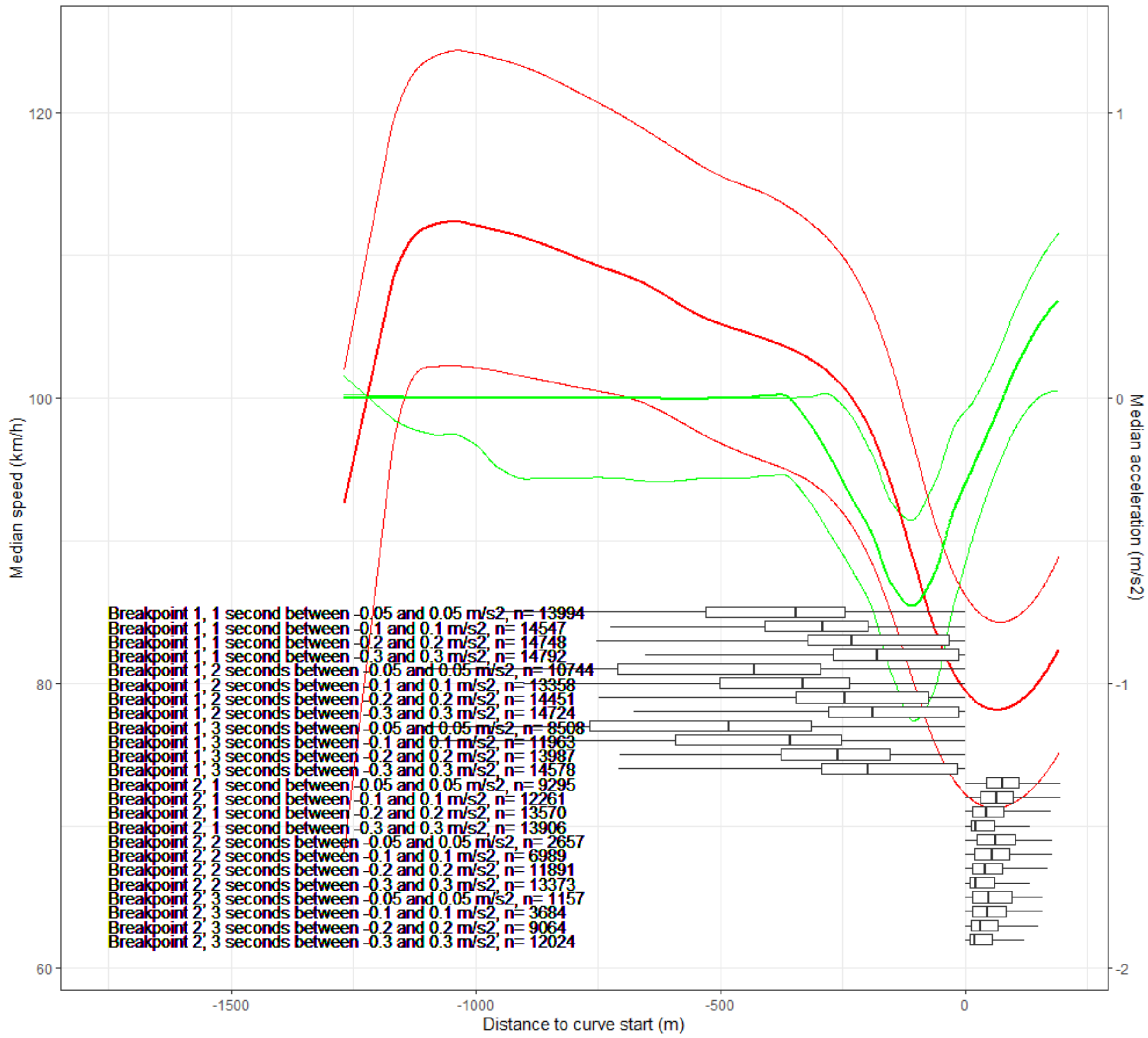


Figure A-5 Summarised speed and acceleration profile based on 14823 unique profiles for a curve with a radius of 150 m and 1 lane. Based on the median acceleration profile, breakpoint 1 should be positioned around 150 m in front of curve start. A threshold of 2 second between -0.1 and 0.1 m/s^2 approaches this the best with the most amount of recorded breakpoints. Breakpoint 2 should be positioned around 75 m after curve start. A threshold of 1 second between -0.1 and 0.1 m/s^2 approaches this the best with the most amount of recorded breakpoints.

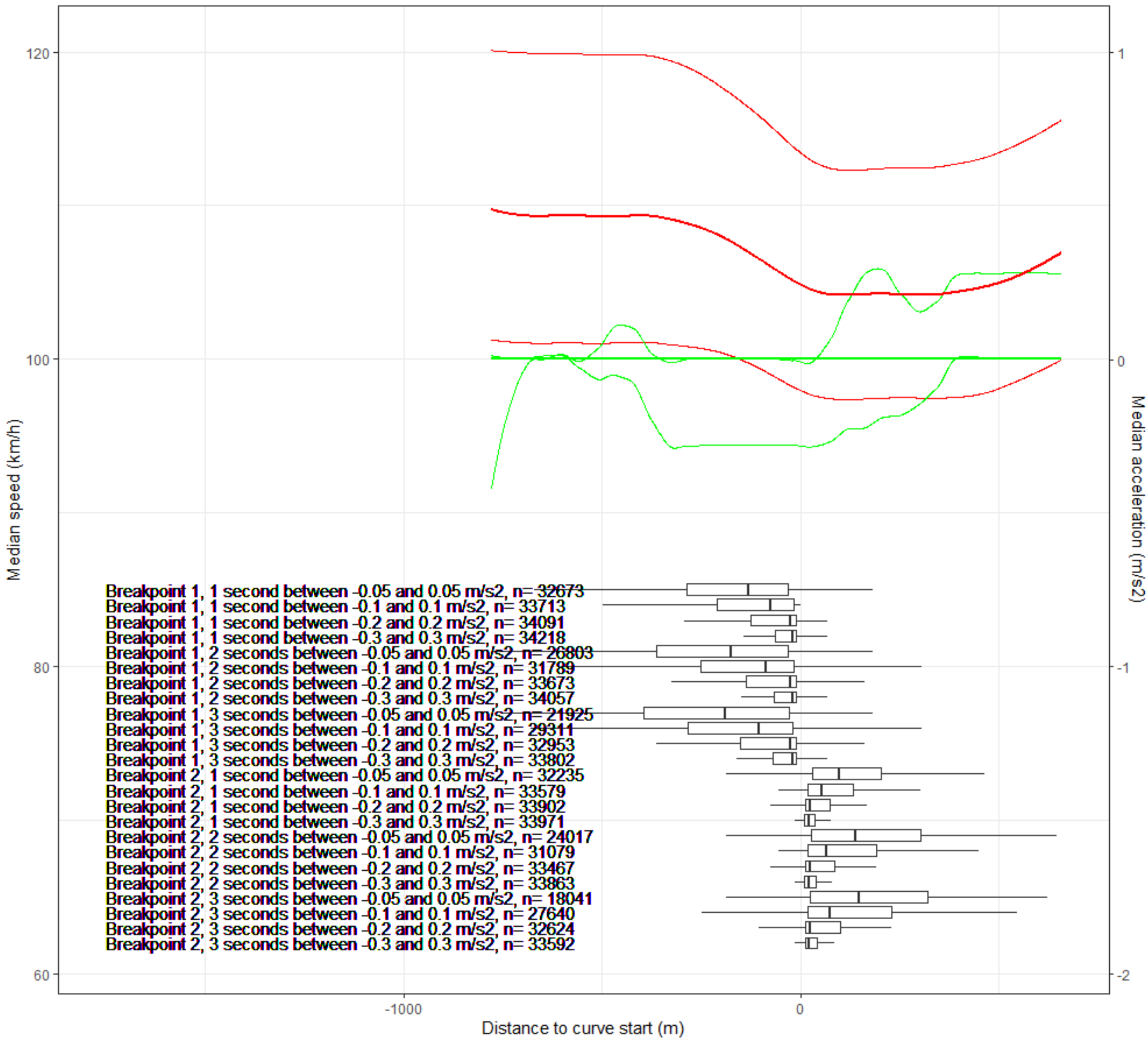


Figure A-6 Summarised speed and acceleration profile based on 34584 unique profiles for a curve with a radius of 400 m and 2 lanes. The median acceleration profile does not show changes in acceleration. Based on the kink in the median speed profile, breakpoint 1 should be positioned around 200 m in front of curve start. A threshold of 3 second between -0.05 and 0.05m/s^2 approaches this the best but loses a lot of recordings, because of its sensitive nature. Increasing the threshold to a range between -0.1 and 0.1 m/s^2 increases the number of recordings much, and remains closest to the kink in the speed profile. Breakpoint 2 should be positioned around 75 m after curve start. A threshold of 1 second between -0.1 and 0.1 m/s^2 approaches this the best with the most amount of recorded breakpoints.

Table A-1 Summary of the best thresholds for each curve

Figure	Best threshold for breakpoint 1	Best threshold for breakpoint 2
A-2	1 second between -0.1 and 0.1 m/s^2	1 second between -0.1 and 0.1 m/s^2
A-3	1 second between -0.05 and 0.05 m/s^2	1 second between -0.1 and 0.1 m/s^2
A-4	1 second between -0.1 and 0.1 m/s^2	1 second between -0.1 and 0.1 m/s^2
A-5	2 seconds between -0.1 and 0.1 m/s^2	1 second between -0.1 and 0.1 m/s^2
A-6	3 seconds between -0.1 and 0.1 m/s^2	1 second between -0.1 and 0.1 m/s^2

Table A-1 summarises the best fitted thresholds for each of the shown curves. It is obvious that for breakpoint 2, a threshold of 1 second between -0.1 and 0.1 m/s^2 should be chosen. For breakpoint 1 however, some different thresholds have been found. It is found that increasing the sensitivity (increasing the amount of seconds, and decreasing the acceleration bandwidth), decreases the amount of recorded breakpoints as well. This suggests that a 1 second threshold should be chosen with an as large as suitable acceleration bandwith, wich is seen at the range of -0.1 and 0.1 m/s^2. This suits most shown speed profiles well. Chosing this threshold will however also include speed profiles which do not have a steady speed before breakpoint 1, but change from an acceleration to a deceleration at breakpoint 1. This leads to the technical definition of breakpoint 1 as the position where deceleration starts.

B Developed Regression Models for Speed Development in the 85th Percentile Speed Modelling

Table B-1 Developed regression models for 85th percentile speeds.

	$v85_{BP1}$	$v85_{BP1}$	$v85_{BP1}$	$v85_{BP1}$	$v85_{CS}$	$v85_{CS}$	$v85_{CS}$	$v85_{CS}$	$v85_{BP2}$	$v85_{BP2}$	$v85_{BP2}$	$v85_{BP2}$	$v85_{BP3}$	$v85_{BP3}$	$v85_{BP3}$	$v85_{BP3}$	$v85_{CE}$	$v85_{CE}$	$v85_{CE}$	$v85_{CE}$	$v85_{BP4}$	$v85_{BP4}$	$v85_{BP4}$	$v85_{BP4}$
Constant	90.38***	88.42***	88.73***	89.87***	-55.33***	-41.34***	-43.28***	-45.69***	-70.04***	-57.74***	-62.12***	-65.33***	-63.69***	-50.87***	-56.58***	-59.88***	-60.57***	-46.65***	-46.37***	-46.73***	63.16***	58.49***	58.57***	62.11***
	(6.55)	(6.63)	(6.65)	(6.72)	(7.05)	(6.41)	(6.54)	(6.79)	(6.40)	(5.92)	(5.43)	(5.71)	(8.48)	(8.55)	(8.03)	(8.61)	(6.06)	(4.98)	(5.17)	(5.45)	(6.80)	(7.14)	(7.30)	(7.61)
ln(Rh)	6.13***	5.78***	5.59***	5.22***	28.95***	25.76***	26.48***	27.09***	31.28***	28.47***	30.11***	30.80***	30.40***	27.47***	29.61***	30.24***	30.12***	26.94***	26.84***	26.97***	10.12***	10.45***	10.43***	9.43***
	(1.17)	(1.19)	(1.21)	(1.27)	(1.27)	(1.22)	(1.34)	(1.44)	(1.15)	(1.13)	(1.11)	(1.21)	(1.53)	(1.63)	(1.64)	(1.82)	(1.09)	(0.95)	(1.06)	(1.15)	(1.26)	(1.25)	(1.33)	(1.46)
nLanes1$_{BP1}$		4.34	4.45	4.54																				
		(2.79)	(2.80)	(2.79)																				
nLanes1						8.11***	8.28***	8.95***		7.13***	7.50***	8.58***		7.43**	7.91***	9.15***		8.07***	8.05***	8.09***				
						(1.66)	(1.65)	(1.70)		(1.53)	(1.37)	(1.43)		(2.21)	(2.03)	(2.15)		(1.29)	(1.31)	(1.36)				
nLanes1$_{BP4}$																						3.83+	3.82+	3.45+
																						(2.00)	(2.01)	(2.01)
length > 250m			1.34				-2.65				-5.98**				-7.79**				0.38				0.11	
			(1.69)				(2.05)				(1.70)				(2.52)				(1.62)				(1.85)	
length in m.				0.00				-0.01+				-0.01**				-0.02**				0.00				0.01
				(0.00)				(0.00)				(0.00)				(0.01)				(0.00)				(0.00)
Num.Obs.	99	99	99	99	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	47	99	99	99	99
R2	0.220	0.239	0.244	0.250	0.920	0.948	0.950	0.952	0.942	0.961	0.970	0.970	0.898	0.919	0.934	0.931	0.944	0.971	0.971	0.971	0.401	0.423	0.423	0.434
R2 Adj.	0.212	0.223	0.220	0.227	0.919	0.946	0.947	0.948	0.941	0.960	0.968	0.968	0.896	0.915	0.929	0.926	0.943	0.969	0.968	0.968	0.395	0.411	0.405	0.416
AIC	703.6	703.1	704.5	703.6	303.7	285.3	285.6	284.3	294.6	277.8	268.0	268.0	321.1	312.3	304.9	306.6	289.5	261.6	263.5	263.6	712.6	710.9	712.9	711.1
BIC	711.4	713.5	717.4	716.6	309.3	292.7	294.8	293.6	300.2	285.2	277.2	277.3	326.6	319.7	314.1	315.9	295.1	269.0	272.8	272.8	720.4	721.3	725.9	724.1
Log.Lik.	-348.790	-347.563	-347.236	-346.801	-148.872	-138.670	-137.775	-137.159	-144.318	-134.906	-128.985	-129.003	-157.528	-152.152	-147.436	-148.324	-141.771	-126.784	-126.754	-126.783	-353.323	-351.466	-351.464	-350.546
F	27.296	15.052	10.206	10.575	519.801	404.235	274.137	281.800	736.472	548.251	463.636	463.269	396.592	249.383	201.770	193.755	761.151	723.764	472.155	471.563	64.962	35.211	23.231	24.259

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B-2 Developed regression models for 50th percentile of positions of breakpoints.

	$pos50_{BP1}$	$pos50_{BP1}$	$pos50_{BP1}$	$pos50_{BP1}$	$pos50_{BP2}$	$pos50_{BP2}$	$pos50_{BP2}$	$pos50_{BP2}$	$pos50_{BP2}$	$pos50_{BP3}$	$pos50_{BP3}$	$pos50_{BP3}$	$pos50_{BP3}$	$pos50_{BP3}$	$pos50_{BP4}$	$pos50_{BP4}$	$pos50_{BP4}$	$pos50_{BP4}$
Constant	-1066.77***	-1051.49***	-1060.96***	-1041.97***	130.41***	123.97**	145.66***	113.41**	85.32***	-122.18*	-89.72	-151.06*	-130.20+	-80.70***	1057.18***	1025.45***	1059.37***	1052.67***
	(60.43)	(61.33)	(60.29)	(60.47)	(31.36)	(35.36)	(32.14)	(36.35)	(8.69)	(56.60)	(63.01)	(57.83)	(66.21)	(15.82)	(82.05)	(87.23)	(83.76)	(87.37)
ln(Rh)	155.10***	157.83***	152.16***	146.28***	-11.04+	-9.57	-16.48*	-6.15		8.53	1.11	18.83	10.84		-158.66***	-156.38***	-159.43***	-157.25***
	(10.83)	(10.99)	(10.99)	(11.41)	(5.65)	(6.74)	(6.45)	(7.72)		(10.19)	(12.01)	(11.61)	(14.07)		(15.14)	(15.28)	(16.07)	(17.71)
$nLanes1_{BP1}$		-33.84																
		(25.87)																
nLanes1						-3.73					18.83							
						(9.15)					(16.30)							
$nLanes1_{BP4}$																26.04		
																(24.43)		
length > 250m			21.53				18.22					-34.50+					3.37	
			(15.59)				(11.06)					(19.90)					(22.58)	
length in m.				0.08*				-0.02	-0.04*				-0.01	0.01				-0.01
				(0.04)				(0.02)	(0.02)				(0.05)	(0.03)				(0.06)
Num.Obs.	99	99	99	99	47	47	47	47	47	47	47	47	47	47	99	99	99	99
R2	0.679	0.685	0.685	0.694	0.078	0.082	0.132	0.096	0.083	0.015	0.044	0.078	0.017	0.003	0.531	0.536	0.531	0.531
R2 Adj.	0.676	0.678	0.679	0.687	0.058	0.040	0.092	0.055	0.063	-0.007	0.001	0.036	-0.028	-0.019	0.526	0.527	0.521	0.521
AIC	1143.5	1143.7	1143.5	1140.9	444.0	445.8	443.2	445.1	443.7	499.5	500.1	498.4	501.4	500.1	1205.7	1206.6	1207.7	1207.7
BIC	1151.3	1154.1	1153.9	1151.3	449.5	453.2	450.6	452.5	449.3	505.1	507.5	505.8	508.8	505.6	1213.5	1217.0	1218.1	1218.1
Log.Lik.	-568.747	-567.872	-567.773	-566.441	-218.993	-218.904	-217.586	-218.537	-218.873	-246.754	-246.052	-245.201	-246.723	-247.038	-599.873	-599.291	-599.862	-599.861
F	205.094	104.155	104.459	108.617	3.824	1.960	3.342	2.337	4.073	0.700	1.020	1.869	0.372	0.152	109.754	55.522	54.335	54.337

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Developed Regression Models for Deceleration development in the 85th Percentile Speed Modelling

Table C-1 Developed regression models for 85th percentile of acceleration.

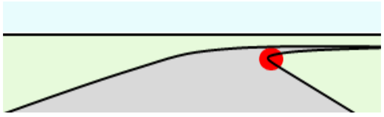
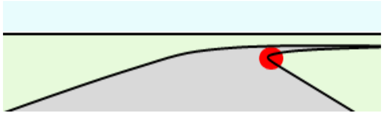
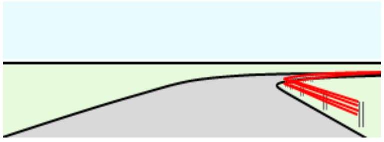
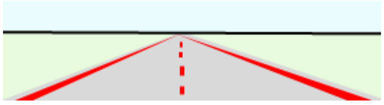
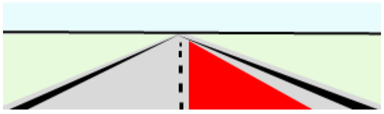
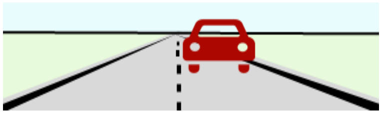
	$a85_{MAXdec}$	$a85_{MAXdec}$	$a85_{MAXdec}$	$a85_{MAXdec}$	$a85_{CS}$	$a85_{CS}$	$a85_{CS}$	$a85_{CS}$	$a85_{CE}$	$a85_{CE}$	$a85_{CE}$	$a85_{CE}$	$a85_{MAXacc}$	$a85_{MAXacc}$	$a85_{MAXacc}$	$a85_{MAXacc}$
Constant	-4.18***	-4.21***	-4.17***	-4.12***	-3.15***	-3.13***	-3.15***	-3.12***	1.46***	1.45***	1.47***	1.44***	3.44***	3.40***	3.45***	3.45***
	(0.21)	(0.23)	(0.21)	(0.21)	(0.17)	(0.19)	(0.17)	(0.17)	(0.10)	(0.10)	(0.10)	(0.10)	(0.13)	(0.13)	(0.13)	(0.13)
ln(Rh)	0.58***	0.59***	0.57***	0.56***	0.46***	0.45***	0.45***	0.44***	-0.19***	-0.19***	-0.20***	-0.19***	-0.50***	-0.49***	-0.51***	-0.51***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)
nLanes1		-0.02				0.02				-0.01				-0.05		
		(0.06)				(0.05)				(0.03)				(0.03)		
length > 250 m			0.04				0.00				0.02				0.02	
			(0.05)				(0.04)				(0.03)				(0.03)	
length in m.				0.00				0.00				0.00				0.00
				(0.00)				(0.00)				(0.00)				(0.00)
Num.Obs.	99	99	99	99	96	96	96	96	96	96	96	96	99	99	99	99
R2	0.712	0.712	0.714	0.720	0.702	0.703	0.702	0.706	0.543	0.544	0.545	0.545	0.827	0.831	0.827	0.827
R2 Adj.	0.709	0.706	0.708	0.714	0.699	0.696	0.696	0.699	0.538	0.534	0.535	0.535	0.825	0.827	0.824	0.824
AIC	20.9	22.8	22.3	20.2	-22.8	-20.9	-20.8	-21.8	-126.3	-124.4	-124.7	-124.7	-76.8	-76.9	-75.0	-74.9
BIC	28.7	33.2	32.7	30.6	-15.1	-10.6	-10.5	-11.5	-118.6	-114.2	-114.5	-114.4	-69.0	-66.5	-64.7	-64.5
Log.Lik.	-7.467	-7.402	-7.167	-6.121	14.376	14.427	14.377	14.896	66.154	66.217	66.371	66.337	41.416	42.457	41.525	41.456
F	239.911	118.940	119.733	123.316	221.883	109.928	109.765	111.464	111.648	55.365	55.691	55.619	464.063	235.539	230.250	229.864

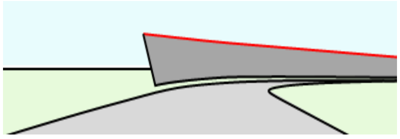
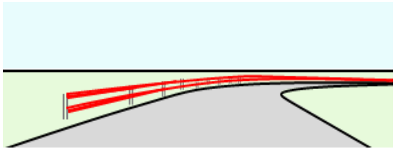
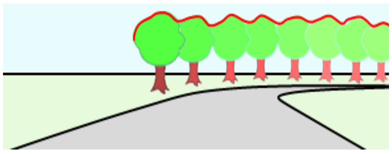
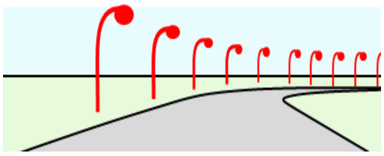
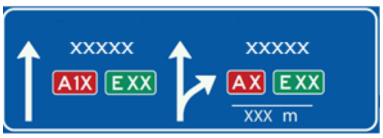
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

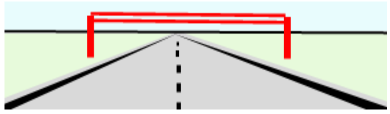
D Labels for the Areas of Interest and Verbalisation in the On-Road Study

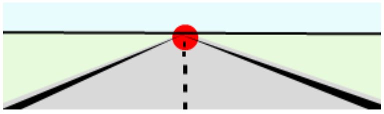
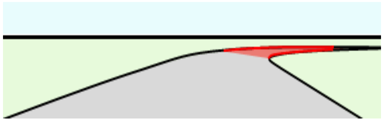
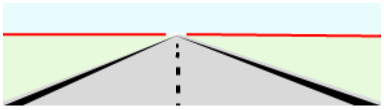
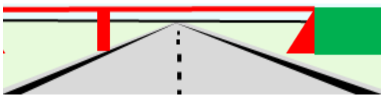
Table D-1 Labels for the Area's of Interest with definitions and pictures.

AoI	**Definition**	**Picture**
In-Car		
Speedometer	The area on the dashboard where the driven speed is shown	
Rear-view mirror	The mirror positioned inside the car to look through the rear window	
Side-view mirror LEFT	External wing mirror on the left side of the car, used to look to the left side behind the car	
Side-view mirror RIGHT	External wing mirror on the right side of the car, used to look to the right side behind the car	
Other	Such as radio, gear-shift, navigation, or body of the car	

AoI	Definition	Picture
Guiding fixations		
Lane tangent point	Any inside curve road marking on tangent point (either closed, open, or block marking). Recognisable as an edge	
Road edge tangent point	Inside curve edge of pavement or crown line (earthworks). Recognisable as an edge	
Obstacle inside curve	Any obstacle located at the inside of a curve, such as guardrail, noise barriers, trees, or bushes which either obscures the sight through a curve or guides the driver	
Marking	All types of marking on the edge of lanes, including noses (not located at the Tangent Point). Recognisable as an edge	
Centre of lane	Including arrow markings	
Car ahead	A car ahead in any lane in front of the participant. When the car is further away than 2 seconds from the driver, it is assumed not to be a guiding fixation, but it is labelled according to the zone the car is located in.	

AoI	**Definition**	**Picture**
Look ahead fixations		
Parallel edges		
Closed elements on the outside of a curve	Such as noise barriers (smooth and straight) Gaze point overlaps with a recognisable edge, so at least with the top of the element or another clear edge within the element	
Guardrail on the outside of a curve	Guardrail or barrier Gaze point overlaps with one of the clearly recognisable edges	
Treeline on the outside of a curve	A wall created by nature; rugged but mainly parallel to the roadway Gaze point overlaps with the top of the treeline, which is recognisable as an edge.	
Objects		
Curve signs (chevron) outside of a curve	A part of this sign is within the gaze point	
Lighting poles	Either inside or outside the curve A part of a lighting pole is within the gaze point	
Route signage	A part of this sign is within the gaze point	

AoI	**Definition**	**Picture**
Gantry	The supporting structure for road signs A part of the gantry is within the gaze point	
Curve warning sign	A part of this sign is within the gaze point	
Curve warning sign (DYNAMIC)	A part of this sign is within the gaze point	
Speed sign (MAX)	A part of this sign is within the gaze point	
Speed sign (MAX) incl curve warning	A part of this sign is within the gaze point	 
Speed sign (ADVICE) incl curve warning	A part of this sign is within the gaze point	 

AoI	Definition	Picture
Zones		
Focus of Expansion	On a tangent, the position where the road disappears on the horizon. In a curve, the position where the optical flow originates from The gaze point is located at this clear, single point, not being an occlusion point	
Far zone (future path)	Patch of road beyond the tangent point, not clearly defined by parallel edges. The road itself is, however, still clearly distinguishable. The gaze point is on the road, beyond the tangent point	
Into curve	Road section not directly visible, beyond the far zone. So, the contours suggest the curve is going there, but no clear edges are recognisable The gaze point is on a surface, not containing edges, beyond the far zone, suggesting the trajectory of the road	
Occlusion point	Point where the roadway disappears. Often being obscured by a vertical element (occlusion point trumps the vertical occluding element in labelling) The gaze point is in the position where the roadway clearly disappears behind a vertical element.	
Horizon	Fixations on the horizon, other than on the Focus of Expansion	
Overpass ahead	All distinguishable parts of an overpass: girders, columns	

AoI	Definition	Picture
Other off road		
Other off road	Everything else, e.g., advertisements, buildings, trains, sky	

Table D-2 Labels for verbalisation with definitions and examples

Label	Definition	Example verbalisations
Driver-related		
Driving style	General mentions about driving style of the participant	I like to go fast through a curve Being (anti)social Having room to manoeuvre It's fun to drive (fast), and I want to accelerate fast Careful when driving and approaching curves
Operating speed	Explicitly mentioning the current operating speed by reading out the speedometer	I'm driving 78 now
Faster than speed sign	Relating the current operating speed to the maximum (or advised) operating speed when the participant is going faster	I'm driving a bit faster now than 80 Usually you can drive faster through a curve
Slower than speed sign	Relating the current operating speed to the maximum (or advised) operating speed when the participant is going slower	I'm allowed to go faster
Unsure about max speed	Stating unawareness about the applicable maximum operating speed	Does this 80 still apply here? I'm looking for speed information
Comfort	Statements about the comfort of driving through the present (or upcoming) curve. This includes relations with lateral acceleration (speed in relation to radius) and drivability.	Adjusting speed for a comfortable drive (I'm braking a bit more) Pre-adjusting speed in order not to brake in the curve This is a nice speed in the curve This feels nice
Familiarity	Statements about the familiarity of the present or upcoming stretch of roadway	I know this stretch very well I usually go to the right here I've never been here before
Traffic-related		
Cars braking	Statements of braking cars downstream of the participant	Cars ahead are braking / slowing down
Traffic volume	Statements about the amount of traffic on the (upcoming) stretch of road	Much traffic / not much traffic

Label	Definition	Example verbalisations
Adjust to traffic	Participant explains his/her driving reactions to other vehicles	I'm decelerating / accelerating to merge What is he doing? Anticipating lane changes of other vehicles I'm not going to overtake, but slow down I'm doing what they are doing Keeping distance
Overtaking	Statements about (the desire to) overtake	I want to go faster (the other one is going too slow) I'm going to overtake
Pre-sorting	Statements about (the desire to) pre-sort	I am going to switch lanes, to be prepared
Lane-keeping	Explicit mentions of not changing lanes	I stay in my lane (to anticipate upcoming events)
Speed related to curve		
Decelerating for curve	Statements about the action of decelerating in (front of) a curve	I'm slowing down for that curve Because of this curve, I'm slowing down
Accelerating after curve	Statements about the action of accelerating out of a curve	We have left the curve, now I'm accelerating Back to speed now
Curve-related		
Curve sighting	Clear statement about sighting and anticipating an upcoming curve	I see an upcoming curve I see other traffic going through a curve
Anticipating radius	Statements about the (upcoming) curve's radius (sharpness)	It is a sharp curve It is not such a sharp curve
Anticipating length	Statements about the (upcoming) curve's length or angle	It is a long turning curve It is a short curve
Curve direction	Statements about the (upcoming) curve's direction	A curve to the left / right
Curve end	Clear statement about sighting and anticipating the end of the present curve.	I can see the end of the curve
Oversight	Statements about being aware of the trajectory of the upcoming road section	I know where the curve is heading I have oversight
No oversight	Statements about being unaware of the trajectory of the upcoming road section	I don't know where the curve is heading, can't see through the curve I have no oversight I can't see what's happening
Speed sign	Explicitly mentioning the presence of a speed sign, either maximum speed or advice, or just the amount of km/h allowed	I notice a speed sign Oh, it's 50 here It is a maximum speed / it's just and advice

Label	**Definition**	**Example verbalisations**
Trees	Explicitly mentioning a treeline on the outside of a curve. Trees in the inside curve obstructing the view are labelled as no oversight	I notice trees
Warning sign	Explicitly mentioning the presence of a curve warning sign	A sign tells me a curve is coming up
Curve sign (chevron)	Explicitly mentioning the presence of a curve chevron sign	I see curve signs
<u>Other cues</u>		
Type of road	Statements of the type of (upcoming) road (section) the participant is on	We're entering the freeway again This doesn't feel like a freeway I wouldn't expect this on a freeway
Number of lanes	Mentions of specific or relative number of lanes Also mentions of lanes based on route signing	Just one lane Too many, more, less lanes
Lane ending	Mentions of a lane ending	Oh, a lane drop is coming up
Special marking	Mentions of all types of special marking	You're not allowed to drive over those markings
Route signing	Mentions about the direction the participant (can) go	I'm looking where to go That's where I need to go (in xxx meters) Junction/off-ramp ahead
Overpass	Mentions of an overpass ahead	I notice an overpass
<u>Pause</u>		
Pause	A clear pause in a full sentence. The second part of the sentence is a clear follow-up of the first part	… uuuhm
<u>Not related to external speed cues</u>		
Non-speed-related	All other, non-speed-related verbalisations, such as distractions, other (traffic) signs, complex situations such as tapers, tiredness, general car	Hey, a nice building, car, train, traffic on other carriageways etc. Good car, stable on the road

E Conditional Probability Tables

This appendix presents the Conditional Probability Tables underlying the tree augmented naïve Bayesian network which is developed in chapter 6.

Table E-1 CPT of node "number of lanes".

	Preceding roadway: connector road							
	Expected safe speed (km/h)							
Number of lanes	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
	Preceding roadway: main carriageway							
	Expected safe speed (km/h)							
Number of lanes	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
	Preceding roadway: merge							
	Expected safe speed (km/h)							
Number of lanes	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
	Preceding roadway: deceleration lane							
	Expected safe speed (km/h)							
Number of lanes	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
	Preceding roadway: fork							
	Expected safe speed (km/h)							
Number of lanes	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
	Preceding roadway: weaving section							
	Expected safe speed (km/h)							
Number of lanes	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 E-2 CPT of node "direction".

	Advice speed: 50 km/h							
	Expected safe speed (km/h)							
Direction	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
	Advice speed: 60 km/h							
	Expected safe speed (km/h)							
Direction	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
	Advice speed: 70 km/h							
	Expected safe speed (km/h)							
Direction	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
	Advice speed: 80 km/h							
	Expected safe speed (km/h)							
Direction	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
	Advice speed: 90 km/h							
	Expected safe speed (km/h)							
Direction	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
	Speed limit: 50 km/h							
	Expected safe speed (km/h)							
Direction	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
	Speed limit: 60 km/h							
	Expected safe speed (km/h)							
Direction	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
	Speed limit: 70 km/h							
	Expected safe speed (km/h)							
Direction	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
	Speed limit: 80 km/h							
	Expected safe speed (km/h)							
Direction	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
	Speed limit: 90 km/h							
	Expected safe speed (km/h)							
Direction	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
	No speed limit							
	Expected safe speed (km/h)							
Direction	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 E-3 CPT of node "Curve sign".

	Advice speed: 50 km/h							
	Expected safe speed (km/h)							
Curve sign	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
	Advice speed: 60 km/h							
	Expected safe speed (km/h)							
Curve sign	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
	Advice speed: 70 km/h							
	Expected safe speed (km/h)							
Curve sign	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
	Advice speed: 80 km/h							
	Expected safe speed (km/h)							
Curve sign	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
	Advice speed: 90 km/h							
	Expected safe speed (km/h)							
Curve sign	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
	Speed limit: 50 km/h							
	Expected safe speed (km/h)							
Curve sign	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
	Speed limit: 60 km/h							
	Expected safe speed (km/h)							
Curve sign	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
	Speed limit: 70 km/h							
	Expected safe speed (km/h)							
Curve sign	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
	Speed limit: 80 km/h							
	Expected safe speed (km/h)							
Curve sign	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
	Speed limit: 90 km/h							
	Expected safe speed (km/h)							
Curve sign	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
	No speed limit							
	Expected safe speed (km/h)							
Curve sign	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 E-4 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
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 E-5 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 E-6 CPT of node "Speed sign".

	Expected safe speed (km/h)							
Speed sign	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 E-7 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
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 E-8 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

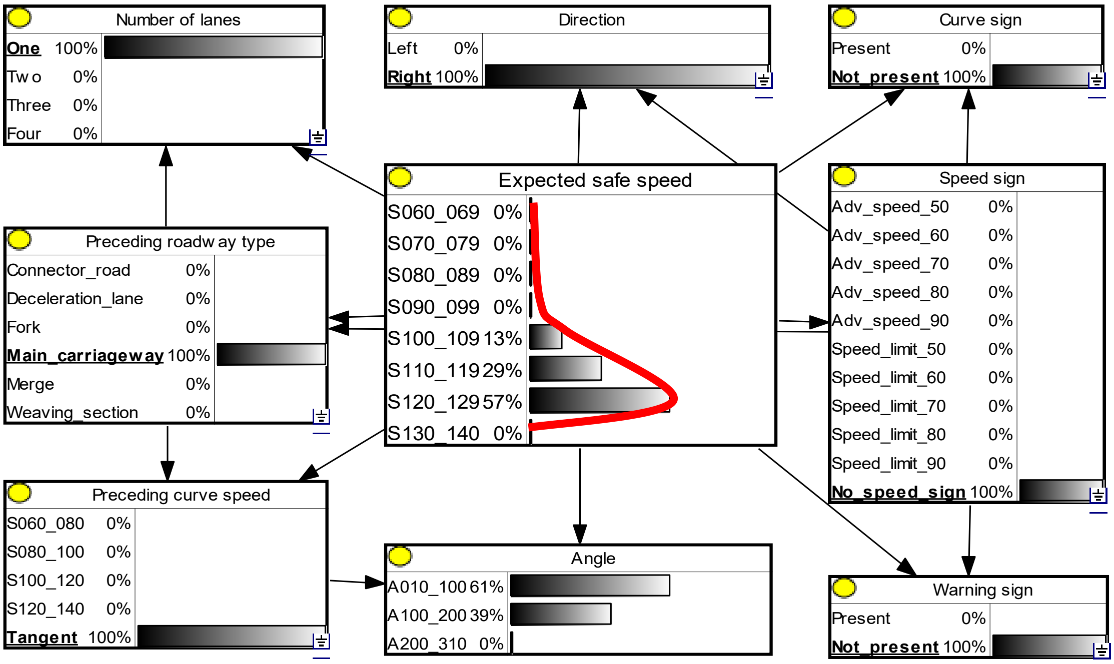
Table E-9 CPT of node "Warning sign".

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

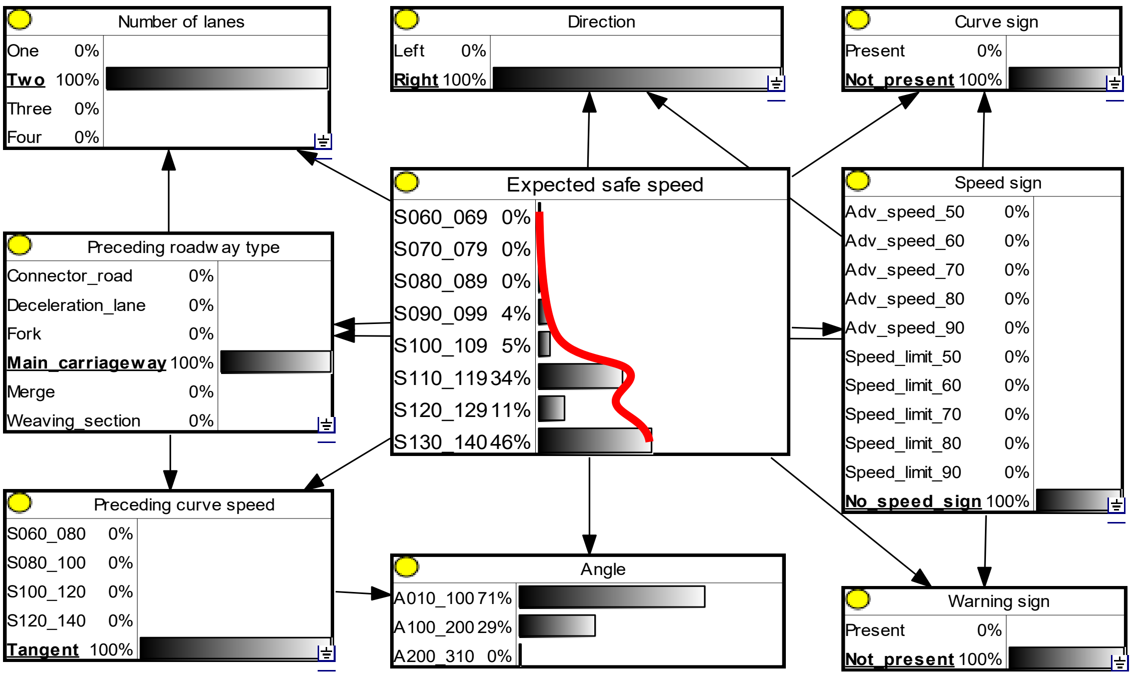
F Some Relevant Safe Speed Expectations

The letters to the left of the TANs represent the letters in Table 6-5.

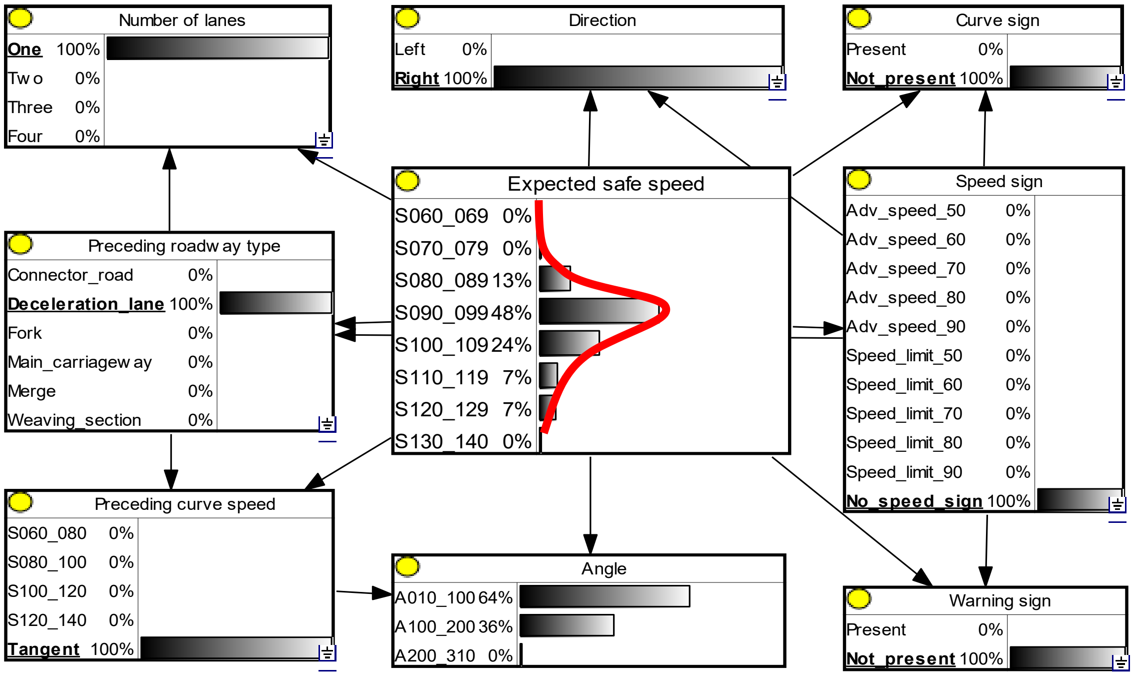
A



B

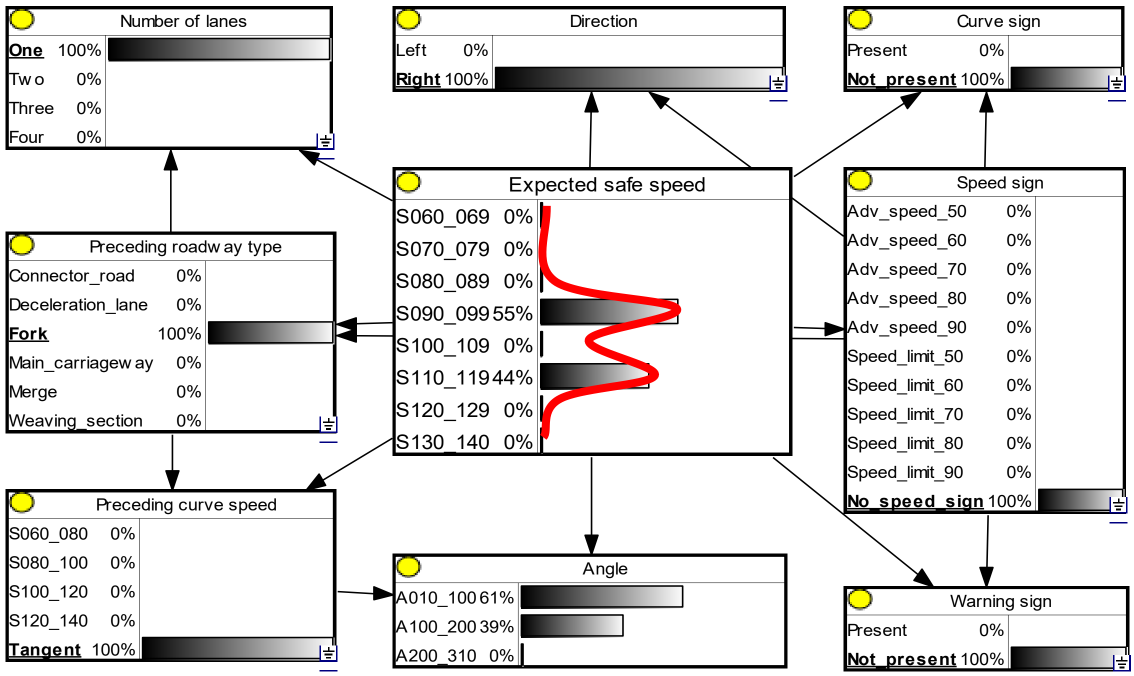


C



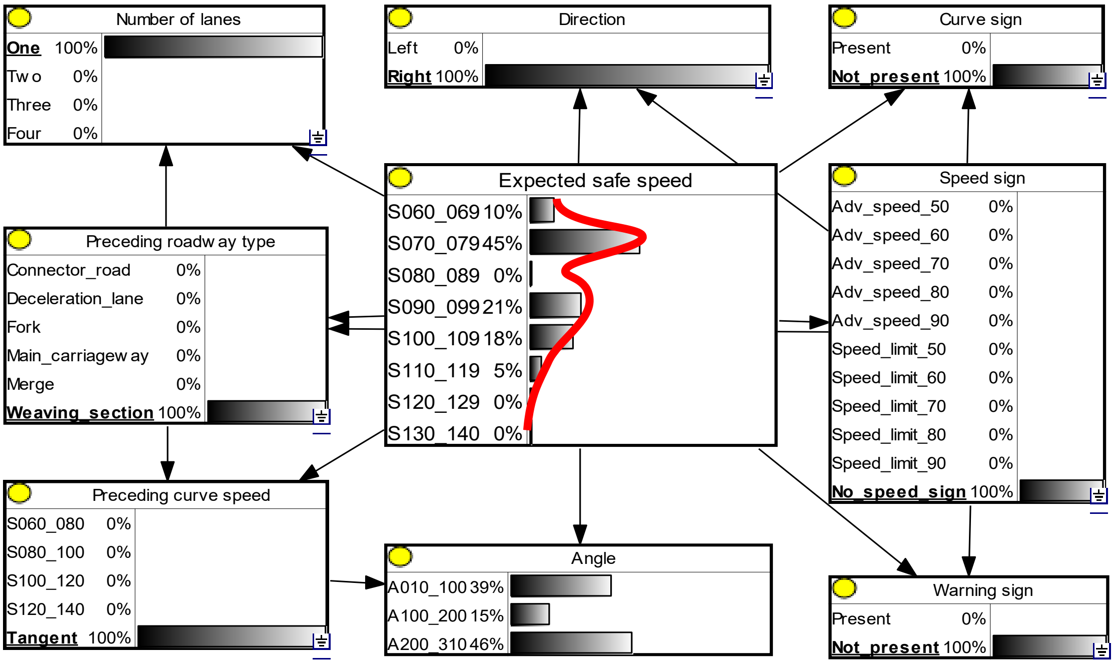
Number of lanes
One 100%
Two 0%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 0%
Not_present 100%
Expected safe speed
S060_069 0%
S070_079 0%
S080_089 13%
S090_099 48%
S100_109 24%
S110_119 7%
S120_129 7%
S130_140 0%
Preceding roadway type
Connector_road 0%
Deceleration_lane 100%
Fork 0%
Main_carriageway 0%
Merge 0%
Weaving_section 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 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

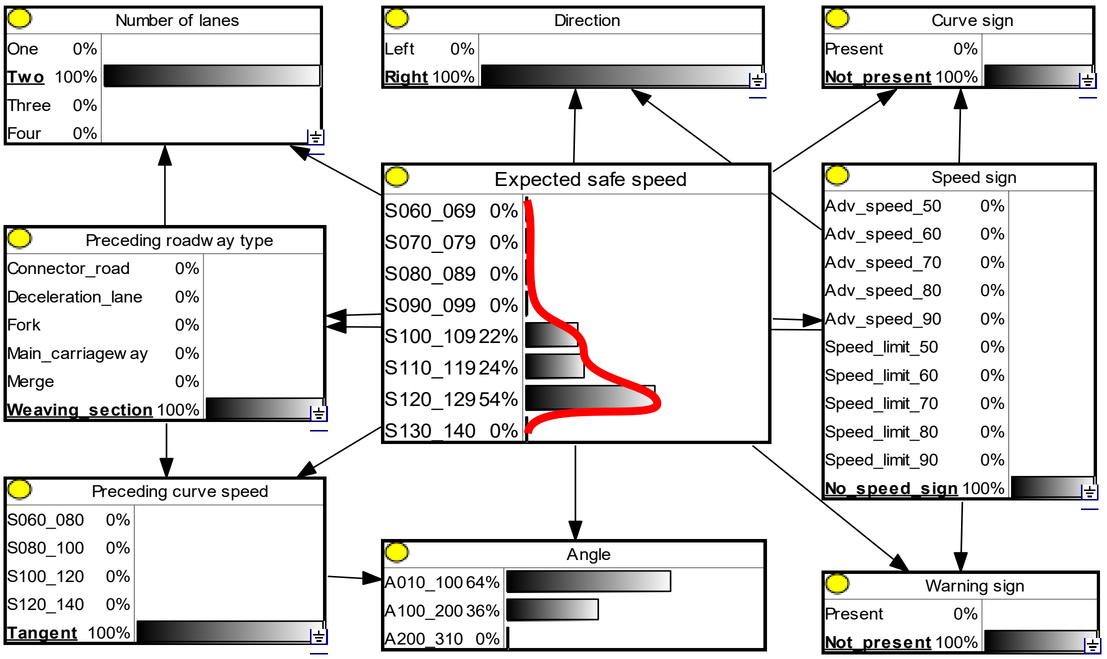


Number of lanes
One 100%
Two 0%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 0%
Not_present 100%
Expected safe speed
S060_069 0%
S070_079 0%
S080_089 0%
S090_099 55%
S100_109 0%
S110_119 44%
S120_129 0%
S130_140 0%
Preceding roadway type
Connector_road 0%
Deceleration_lane 0%
Fork 100%
Main_carriageway 0%
Merge 0%
Weaving_section 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 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%
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 39%
A100_200 15%
A200_310 46%
Warning sign
Present 0%
Not_present 100%

F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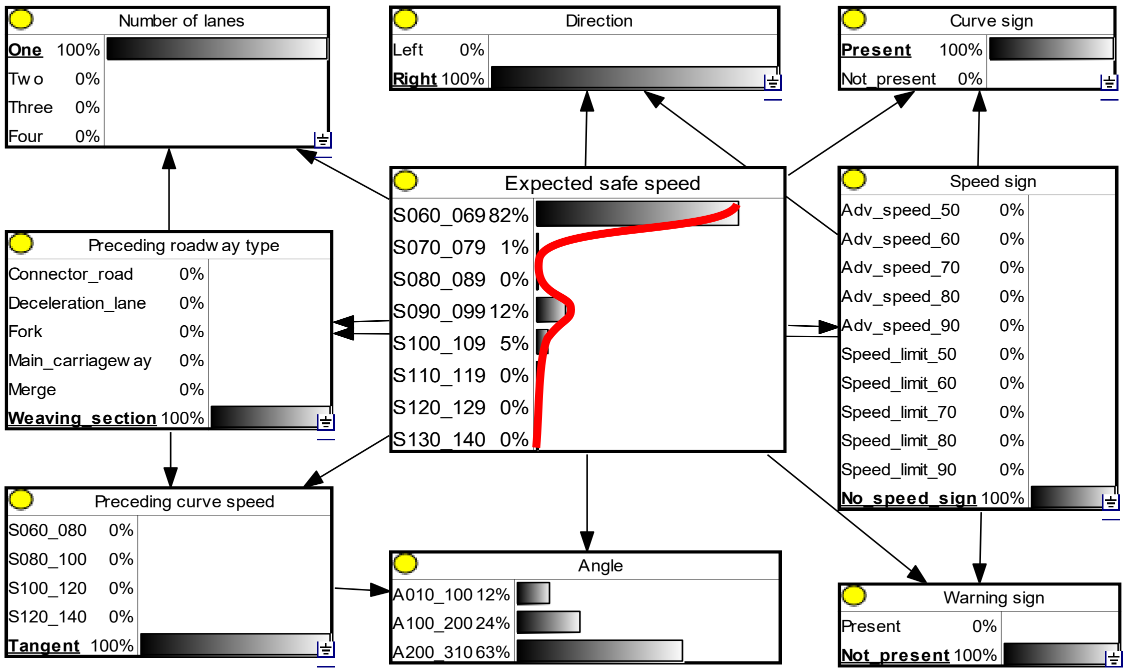
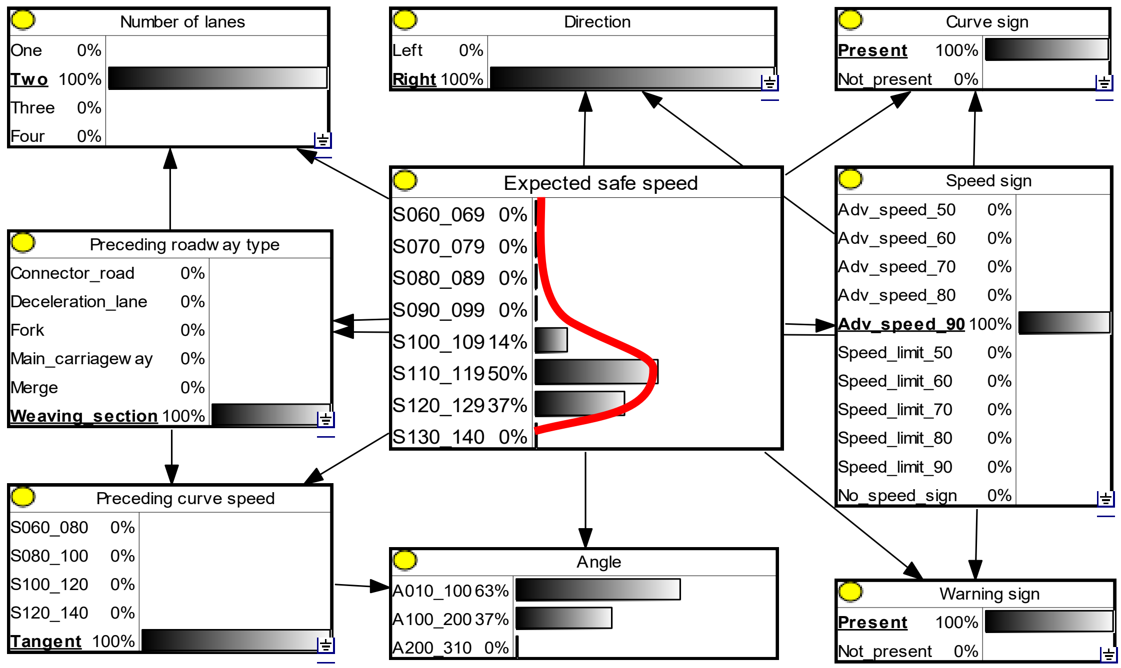
One 0%
Two 100%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 0%
Not_present 100%
Expected safe speed
S060_069 0%
S070_079 0%
S080_089 0%
S090_099 0%
S100_109 22%
S110_119 24%
S120_129 54%
S130_140 0%
Speed sign
Adv_speed_50 0%
Adv_speed_60 0%
Adv_speed_70 0%
Adv_speed_80 0%
Adv_speed_90 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 64%
A100_200 36%
A200_310 0%
Warning sign
Present 0%
Not_present 100%

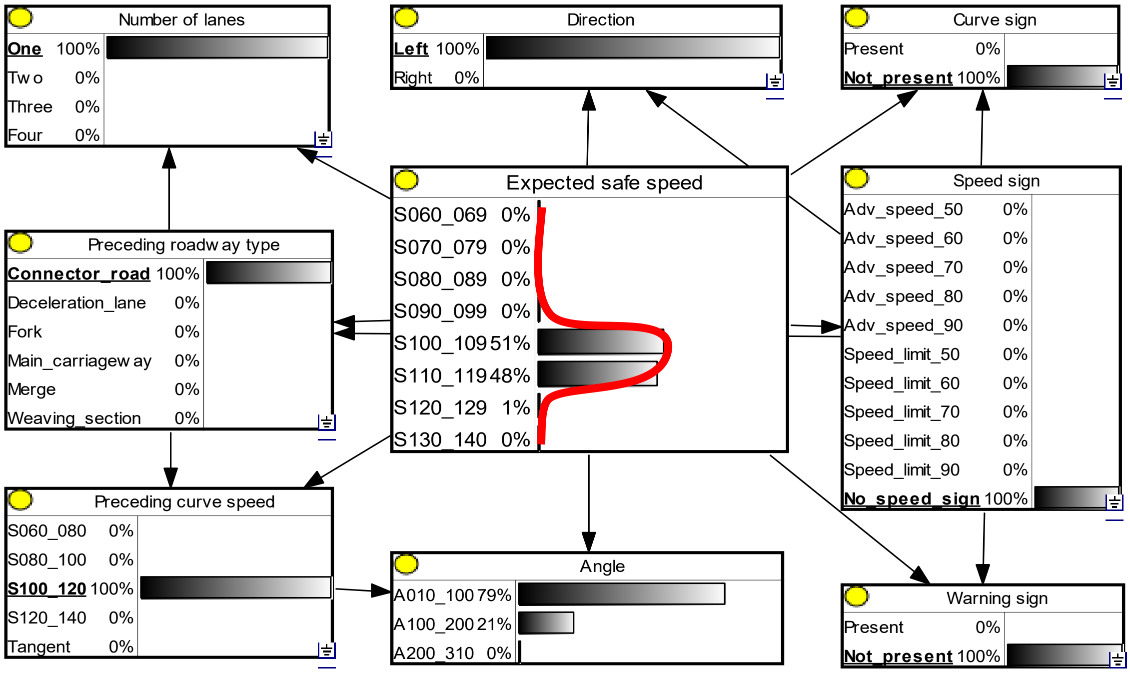
G


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%

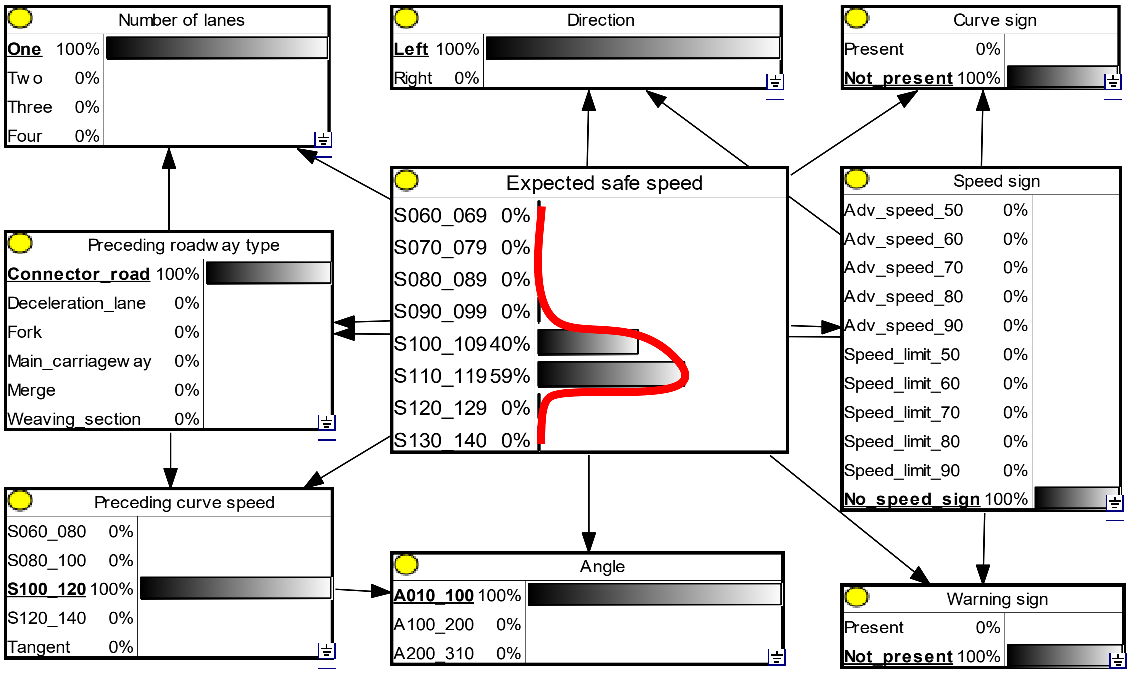
H


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%

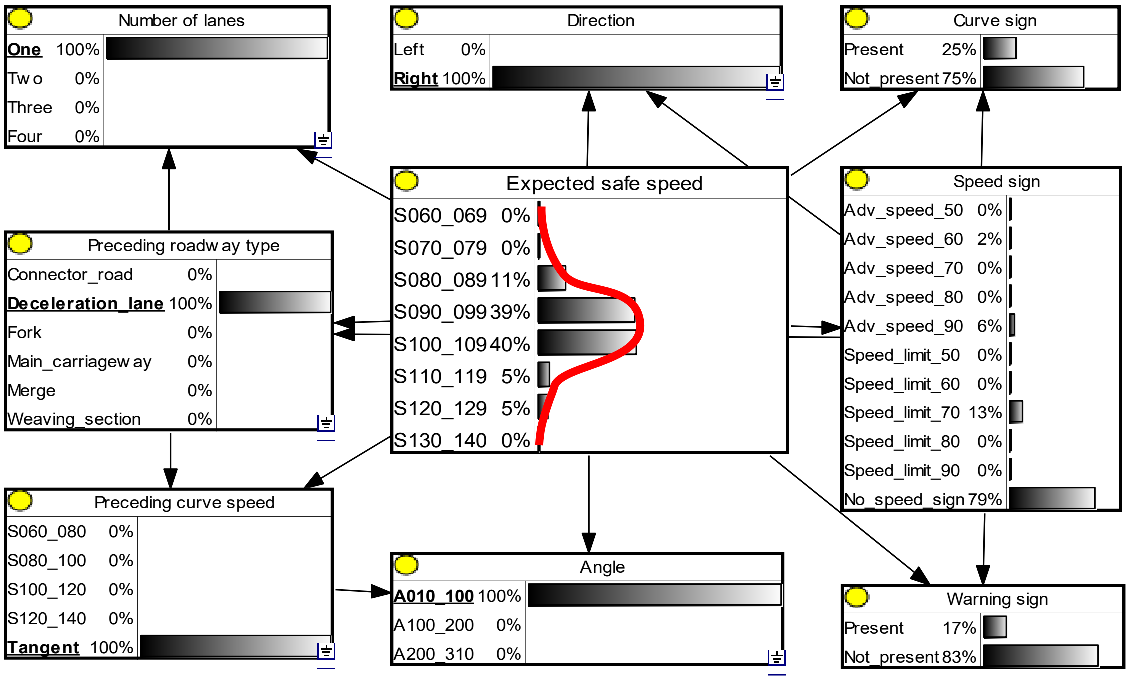
I


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%

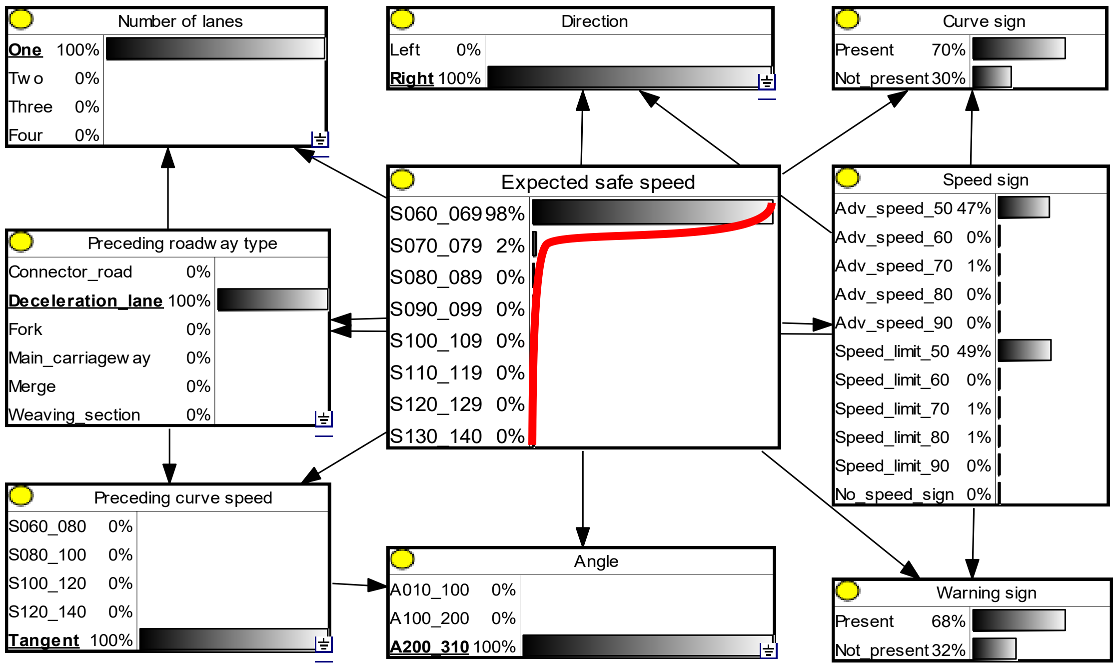
J


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%

K


Number of lanes
One 100%
Two 0%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 25%
Not_present 75%
Expected safe speed
S060_069 0%
S070_079 0%
S080_089 11%
S090_099 39%
S100_109 40%
S110_119 5%
S120_129 5%
S130_140 0%
Speed sign
Adv_speed_50 0%
Adv_speed_60 2%
Adv_speed_70 0%
Adv_speed_80 0%
Adv_speed_90 6%
Speed_limit_50 0%
Speed_limit_60 0%
Speed_limit_70 13%
Speed_limit_80 0%
Speed_limit_90 0%
No_speed_sign 79%
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_100 100%
A100_200 0%
A200_310 0%
Warning sign
Present 17%
Not_present 83%

L


Number of lanes
One 100%
Two 0%
Three 0%
Four 0%
Direction
Left 0%
Right 100%
Curve sign
Present 70%
Not_present 30%
Expected safe speed
S060_069 98%
S070_079 2%
S080_089 0%
S090_099 0%
S100_109 0%
S110_119 0%
S120_129 0%
S130_140 0%
Speed sign
Adv_speed_50 47%
Adv_speed_60 0%
Adv_speed_70 1%
Adv_speed_80 0%
Adv_speed_90 0%
Speed_limit_50 49%
Speed_limit_60 0%
Speed_limit_70 1%
Speed_limit_80 1%
Speed_limit_90 0%
No_speed_sign 0%
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 0%
A100_200 0%
A200_310 100%
Warning sign
Present 68%
Not_present 32%

G Supplementary Data

The research of this dissertation generated several data sets. This data is available through the 4TU/Researchdata repository. The datasets available are:

- *Data underlying the publication: How do Dutch drivers perceive horizontal curves on freeway interchanges and which cues influence their speed choice?* This dataset contains the raw output from the survey in chapter 2. The dataset can be found at: https://doi.org/10.4121/68fb060e-226f-4aad-903e-c924b498ff86
- *Data underlying the publication: Speed behaviour upon approaching freeway curves.* This dataset contains the aggregated database used for the analysis of the individual speed profiles in chapter 3, along a file explaining the different variables in the database. The dataset can be found at: https://doi.org/10.4121/e298fc48-daa8-436f-a5f7-a12030f6ebed
- *Data underlying the publication: Speed development at freeway curves based on high frequency floating car data.* This dataset contains the aggregated database used for the generation of the parsimonious models in chapter 4. The variables in the database are explained in an additional sheet. The dataset can be found at: https://doi.org/10.4121/5cad48c2-2767-49a2-9e2c-cc7f84ab9182
- *Which Visual Cues do Drivers Use to Anticipate and Slow Down in Freeway Curve Approach? An Eye-Tracking and Think-Aloud On-road Study - Dataset.* The collected data in the on-road study in chapter 5 is shared in this dataset and contains:
    - GPS data of the researched sections
    - Filtered Eye-tracking data, containing the fixations, timestamps and AoI labels
    - Verbalisations
    - 6 muted video's of the HD-camera from the eye-tracker, containing fixation data (a video for each curve, from a single participant)
    - Output from the questionnaires

  The dataset can be found at: https://doi.org/10.4121/21069820.

The dataset used in the Bayesian Belief Network (chapter 6), will be published once the paper is published. The data is however derived from the data used in chapters 3 and 4.

References

Aarts, L., & Van Schagen, I. (2006). Driving speed and the risk of road crashes: A review. *Accident Analysis and Prevention, 38*(2), 215-224. doi:https://doi.org/10.1016/j.aap.2005.07.004

Ahie, L. M., Charlton, S. G., & Starkey, N. J. (2015). The role of preference in speed choice. *Transportation Research Part F: Traffic Psychology and Behaviour, 30*, 66-73. doi:https://doi.org/10.1016/j.trf.2015.02.007

Alexander, G. J., & Lunenfeld, H. (1986). *Driver expectancy in highway design and traffic operations*: US Department of Transportation, Federal Highway Administration, Office of Traffic Operations.

Altamira, A., García Ramírez, Y., Echaveguren, T., & Marcet, J. (2014). *Acceleration and Deceleration Patterns on Horizontal Curves and Their Tangents on Two-Lane Rural Roads*. Paper presented at the Transportation Research Board 93rd Annual Meeting, Washington.

Bahill, A. T., & LaRitz, T. (1984). Why can't batters keep their eyes on the ball? *American Scientist, 72*(3), 249-253.

Bakker, H. B., & Springer, J. F. (1961). De belijning van de weg III Bogen in horizontale wegvakken. *Wegen*, 202-209.

Bella, F. (2009). Can driving simulators contribute to solving critical issues in geometric design? *Transportation Research Record, 2138*, 120-126. doi:https://doi.org/10.3141/2138-16

Bella, F. (2013). Driver perception of roadside configurations on two-lane rural roads: Effects on speed and lateral placement. *Accident Analysis & Prevention, 50*, 251-262. doi:https://doi.org/10.1016/j.aap.2012.04.015

Bella, F. (2014). Driver Performance Approaching and Departing Curves: Driving Simulator Study. *Traffic Injury Prevention, 15*(3), 310-318. doi:https://doi.org/10.1080/15389588.2013.813022

Bella, F. (2015). Coordination of horizontal and sag vertical curves on two-lane rural roads: Driving simulator study. *IATSS Research, 39*(1), 51-57. doi:https://doi.org/10.1016/j.iatssr.2015.02.002

Blumentrath, C., & Tveit, M. S. (2014). Visual characteristics of roads: A literature review of people's perception and Norwegian design practice. *Transportation Research Part A: Policy and Practice, 59*, 58-71. doi:https://doi.org/10.1016/j.tra.2013.10.024

Bobermin, M. P., Silva, M. M., & Ferreira, S. (2021). Driving simulators to evaluate road geometric design effects on driver behaviour: A systematic review. *Accident Analysis & Prevention, 150*, 105923. doi:https://doi.org/10.1016/j.aap.2020.105923

Borowsky, A., Shinar, D., & Parmet, Y. (2008). Sign location, sign recognition, and driver expectancies. *Transportation Research Part F: Traffic Psychology and Behaviour, 11*(6), 459-465. doi:https://doi.org/10.1016/j.trf.2008.06.003

Borsos, A., Birth, S., & Vollpracht, H. J. (2015, 19-21 Oct. 2015). *The role of human factors in road design.* Paper presented at the 2015 6th IEEE International Conference on Cognitive Infocommunications (CogInfoCom).

Broeren, P. (2002). *Evaluating Sight Distances in Highway Design, a Practical Tool*. Paper presented at the TRB Symposium on Visualization in Transportation, Salt Lake City.

Brummelaar, T. T. (1975). Where are the Kinks in the Alignment? *Transportation Research Record, 556*, 35-50.

Burdett, B. R. D., Charlton, S. G., & Starkey, N. J. (2019). Mind wandering during everyday driving: An on-road study. *Accident Analysis & Prevention, 122*, 76-84. doi:https://doi.org/10.1016/j.aap.2018.10.001

Cafiso, S., & Cerni, G. (2012). New approach to defining continuous speed profile models for two-lane rural roads. *Transportation Research Record*(2309), 157-167. doi:https://doi.org/10.3141/2309-16

Cafiso, S., & La Cava, G. (2009) Driving performance, alignment consistency, and road safety. In. *Transportation Research Record* (pp. 1-8).

Calvi, A. (2015). A Study on Driving Performance Along Horizontal Curves of Rural Roads. *Journal of Transportation Safety and Security, 7*(3), 243-267. doi:https://doi.org/10.1080/19439962.2014.952468

Calvi, A. (2015). A Study on Driving Performance Along Horizontal Curves of Rural Roads. *Journal of Transportation Safety & Security, 7*(3), 243-267. doi:10.1080/19439962.2014.952468

Calvi, A., Bella, F., & D'Amico, F. (2018). Evaluating the effects of the number of exit lanes on the diverging driver performance. *Journal of Transportation Safety and Security, 10*(1-2), 105-123. doi:https://doi.org/10.1080/19439962.2016.1208313

Calvi, A., D'Amico, F., Bianchini Ciampoli, L., & Ferrante, C. (2019). Evaluating the effectiveness of perceptual treatments on sharp curves: a driving simulator study. *Traffic Injury Prevention, 20*(sup2), S13-S19. doi:https://doi.org/10.1080/15389588.2019.1669789

Campbell, J. L., Lichty, M. G., Brown, J. L., Richard, C. M., Graving, J. S., Graham, J., . . . Harwood, D. (2012). *Human factors guidelines for road systems* (J. L. Campbell Ed. 2nd ed ed.). Washington, D.C: Transportation Research Board.

Casal, G., Santamarina, D., & Vázquez-Méndez, M. E. (2017). Optimization of horizontal alignment geometry in road design and reconstruction. *Transportation Research Part C: Emerging Technologies, 74*, 261-274. doi:https://doi.org/10.1016/j.trc.2016.11.019

Chanales, A. J. H., Oza, A., Favila, S. E., & Kuhl, B. A. (2017). Overlap among Spatial Memories Triggers Repulsion of Hippocampal Representations. *Current Biology, 27*(15), 2307-2317.e2305. doi:https://doi.org/10.1016/j.cub.2017.06.057

Charlton, S. G. (2004). Perceptual and attentional effects on drivers' speed selection at curves. *Accident Analysis & Prevention, 36*(5), 877-884. doi:https://doi.org/10.1016/j.aap.2003.09.003

Charlton, S. G. (2007). The role of attention in horizontal curves: A comparison of advance warning, delineation, and road marking treatments. *Accident Analysis and Prevention, 39*(5), 873-885. doi:https://doi.org/10.1016/j.aap.2006.12.007

Charlton, S. G., & Starkey, N. J. (2011). Driving without awareness: The effects of practice and automaticity on attention and driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 14*(6), 456-471. doi:https://doi.org/10.1016/j.trf.2011.04.010

Charlton, S. G., & Starkey, N. J. (2013). Driving on familiar roads: Automaticity and inattention blindness. *Transportation Research Part F: Traffic Psychology and Behaviour, 19*, 121-133. doi:https://doi.org/10.1016/j.trf.2013.03.008

Charlton, S. G., & Starkey, N. J. (2017a). Drivers' mental representations of familiar rural roads. *Journal of Environmental Psychology, 50*, 1-8. doi:https://doi.org/10.1016/j.jenvp.2017.01.003

Charlton, S. G., & Starkey, N. J. (2017b). Driving on urban roads: How we come to expect the 'correct' speed. *Accident Analysis & Prevention, 108*, 251-260. doi:https://doi.org/10.1016/j.aap.2017.09.010

Charlton, S. G., & Starkey, N. J. (2018a). Attention and awareness in everyday driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 57*, 1-3. doi:https://doi.org/10.1016/j.trf.2018.04.014

Charlton, S. G., & Starkey, N. J. (2018b). Memory for everyday driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 57*, 129-138. doi:https://doi.org/10.1016/j.trf.2017.06.007

Chavent, M., Kuentz-Simonet, V., Liquet, B., & Saracco, J. (2012). ClustOfVar: An R package for the clustering of variables. *Journal of Statistical Software, 50*(13), 1-16. doi:https://doi.org/10.18637/jss.v050.i13

Chen, S. H., & Pollino, C. A. (2012). Good practice in Bayesian network modelling. *Environmental Modelling & Software, 37*, 134-145. doi:https://doi.org/10.1016/j.envsoft.2012.03.012

Čičković, M. (2016). Influence of Human Behaviour on Geometric Road Design. *Transportation Research Procedia, 14*, 4364-4373. doi:https://doi.org/10.1016/j.trpro.2016.05.358

Cleveland, W. S., Grosse, E., & Shyu, W. M. (1992). Local Regression Models. In *Statistical Models in S*: Routledge.

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). New York: Routledge.

Colombaroni, C., Fusco, G., & Isaenko, N. (2020). *Analysis of Road Safety Speed from Floating Car Data.* Paper presented at the Transportation Research Procedia.

Costa, A. T., Figueira, A. C., & Larocca, A. P. C. (2022). An eye-tracking study of the effects of dimensions of speed limit traffic signs on a mountain highway on driverś perception. *Transportation Research Part F: Traffic Psychology and Behaviour, 87*, 42-53. doi:https://doi.org/10.1016/j.trf.2022.03.013

Costa, M., Simone, A., Vignali, V., Lantieri, C., Bucchi, A., & Dondi, G. (2014). Looking behavior for vertical road signs. *Transportation Research Part F: Traffic Psychology and Behaviour, 23*, 147-155. doi:https://doi.org/10.1016/j.trf.2014.01.003

Coutton-Jean, C., Mestre, D. R., Goulon, C., & Bootsma, R. J. (2009). The role of edge lines in curve driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 12*(6), 483-493. doi:https://doi.org/10.1016/j.trf.2009.04.006

Crundall, D., & Underwood, G. (2011). Chapter 11 - Visual Attention While Driving: Measures of Eye Movements Used in Driving Research. In B. E. Porter (Ed.), *Handbook of Traffic Psychology* (pp. 137-148). San Diego: Academic Press.

Davidse, R. J., Duijvenvoorde, K. v., & Louwerse, W. J. R. (2020). Fatal road crashes on national roads in 2019; Analysis of crash and injury factors and resulting potential countermeasures. *SWOV, Leidschendam*(R-2020-29), 45.

de Haas, B. (2017). *Sexuality Education in Uganda: teachers' reasoning in a 'morally upright' context.* (PhD dissertation). University of Groningen, Groningen.

de Waard, D., Steyvers, F. J. J. M., & Brookhuis, K. A. (2004). How much visual road information is needed to drive safely and comfortably? *Safety Science, 42*(7), 639-655. doi:https://doi.org/10.1016/j.ssci.2003.09.002

Deng, Z., Chu, D., Wu, C., He, Y., & Cui, J. (2018). Curve safe speed model considering driving style based on driver behaviour questionnaire. *Transportation Research Part F: Traffic Psychology and Behaviour*. doi:10.1016/j.trf.2018.02.007

Dhahir, B., & Hassan, Y. (2019a). Framework for Reliability-Based, Safety-Explicit Horizontal Curve Design using Naturalistic Driving Data. *Transportation Research Record*. doi:https://doi.org/10.1177/0361198119838853

Dhahir, B., & Hassan, Y. (2019b). Modeling Speed and Comfort Threshold on Horizontal Curves of Rural Two-Lane Highways Using Naturalistic Driving Data. *Journal of Transportation Engineering, Part A: Systems, 145*(6), 04019025.

Dias, C., Oguchi, T., & Wimalasena, K. (2018). Drivers' Speeding Behavior on Expressway Curves: Exploring the Effect of Curve Radius and Desired Speed. *Transportation Research Record, 2672*, 48 –60. doi:https://doi.org/10.1177/0361198118778931

Dijkstra, J. (2008). *Gevaarlijke Wegen: Veilige Wegen? - Een onderzoek naar de invloed van inrichting van de openbare ruimte op het gedrag van weggebruikers.* (MSc-thesis). Rijksuniversiteit Groningen, Groningen.

Domenichini, L., Paliotto, A., Meocci, M., & Branzi, V. (2022). Application and Evaluation of a Non-Accident-Based Approach to Road Safety Analysis Based on Infrastructure-Related Human Factors. *Sustainability, 14*, 662. doi:https://doi.org/10.3390/su14020662

Donnell, E., Wood, J., Himes, S., & Torbic, D. (2016). Use of side friction in horizontal curve design: A margin of safety assessment. *Transportation Research Record, 2588*, 172-180. doi:https://doi.org/10.3141/2588-07

Druzdzel, M. J. (1999). *SMILE: Structural Modeling, Inference, and Learning Engine and GeNIe: a development environment for graphical decision-theoretic models.* Paper presented at the Aaai/Iaai.

Echaveguren, T., Henríquez, C., & Jiménez-Ramos, G. (2020). Longitudinal acceleration models for horizontal reverse curves of two-lane rural roads. *Baltic Journal of Road and Bridge Engineering, 15*(1), 103-125. doi:https://doi.org/10.7250/bjrbe.2020-15.463

Elvik, R. (2022). Which is the more important for road safety—road design or driver behavioural adaptation? *Traffic Safety Research, 2*, 000009. doi:https://doi.org/10.55329/pvir7839

Endsley, M. R. (1995). Toward a Theory of Situation Awareness in Dynamic Systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 37*(1), 32-64. doi:https://doi.org/10.1518/001872095779049543

Engström, J., Bärgman, J., Nilsson, D., Seppelt, B., Markkula, G., Piccinini, G. B., & Victor, T. (2018). Great expectations: a predictive processing account of automobile driving. *Theoretical Issues in Ergonomics Science, 19*(2), 156-194. doi:https://doi.org/10.1080/1463922X.2017.1306148

Ericsson, K. A., & Fox, M. C. (2011). Thinking Aloud Is Not a Form of Introspection but a Qualitatively Different Methodology: Reply to Schooler (2011). *Psychological Bulletin, 137*(2), 351-354. doi:https://doi.org/10.1037/a0022388

Ericsson, K. A., & Simon, H. A. (1980). Verbal reports as data. *Psychological Review, 87*(3), 215-251. doi:https://doi.org/10.1037/0033-295X.87.3.215

Evans, J. S. B. T. (2003). In two minds: dual-process accounts of reasoning. *Trends in Cognitive Sciences, 7*(10), 454-459. doi:https://doi.org/10.1016/j.tics.2003.08.012

Farah, H., Daamen, W., & Hoogendoorn, S. (2019). How do drivers negotiate horizontal ramp curves in system interchanges in the Netherlands? *Safety Science, 119*, 58-69. doi:https://doi.org/10.1016/j.ssci.2018.09.016

Farah, H., van Beinum, A., & Daamen, W. (2017). Empirical Speed Behavior on Horizontal Ramp Curves in Interchanges in the Netherlands. *Transportation Research Record: Journal of the Transportation Research Board, 2618*, 38-47. doi:https://doi.org/10.3141/2618-04

Fazekas, P., & Overgaard, M. (2018). A Multi-Factor Account of Degrees of Awareness. *Cognitive Science, 42*(6), 1833-1859. doi:https://doi.org/10.1111/cogs.12478

Feldman, J. (2013). Bayesian models of perceptual organization. *Handbook of perceptual organization*, 1008–1026.

Feng, F., Bao, S., Sayer, J. R., Flannagan, C., Manser, M., & Wunderlich, R. (2017). Can vehicle longitudinal jerk be used to identify aggressive drivers? An examination using naturalistic driving data. *Accident Analysis & Prevention, 104*, 125-136. doi:https://doi.org/10.1016/j.aap.2017.04.012

Fildes, B. N., & Triggs, T. J. (1985). The on effect of changes in curve geometry magnitude estimates of road-like perspective curvature. *Perception & Psychophysics, 37*(3), 218-224.

Fitzpatrick, K., Carlson, P., Brewer, M., & Wooldridge, M. (2003). *Design speed, operating speed, and posted speed limit practices*. Retrieved from Washington, D.C.:

Fitzpatrick, K., & Kahl, K. (1992). *A Historical and Literature Review of Horizontal Curve Design*. Austin, Texas: Texas Transportation Institute.

Friedman, N., Geiger, D., & Goldszmidt, M. (1997). Bayesian network classifiers. *Machine learning, 29*, 131-163.

Frost, R., Armstrong, B. C., Siegelman, N., & Christiansen, M. H. (2015). Domain generality versus modality specificity: The paradox of statistical learning. *Trends in Cognitive Sciences, 19*(3), 117-125. doi:https://doi.org/10.1016/j.tics.2014.12.010

Geisler, W. S., Perry, J. S., Super, B. J., & Gallogly, D. P. (2001). Edge co-occurrence in natural images predicts contour grouping performance. *Vision Research, 41*(6), 711–724.

. GeNIe Modeler (Version 4.0.R2). (2022): BayesFusion, LLC.

Geurts, L. S., Cooke, J. R. H., van Bergen, R. S., & Jehee, J. F. M. (2022). Subjective confidence reflects representation of Bayesian probability in cortex. *Nature Human Behaviour, 6*(2), 294-305. doi:https://doi.org/10.1038/s41562-021-01247-w

Ghosh, V. E., & Gilboa, A. (2014). What is a memory schema? A historical perspective on current neuroscience literature. *Neuropsychologia, 53*, 104-114. doi:https://doi.org/10.1016/j.neuropsychologia.2013.11.010

Gibson, J. J. (1950). *The Perception Of The Visual World* (Vol. 60): Houghton Mifflin.

Gibson, J. J., & Crooks, L. E. (1938). A Theoretical Field-Analysis of Automobile-Driving. *The American Journal of Psychology, 51*(3), 453. doi:https://doi.org/10.2307/1416145

Graves, K. N., Sherman, B. E., Huberdeau, D., Damisah, E., Quraishi, I. H., & Turk-Browne, N. B. (2022). Remembering the pattern: A longitudinal case study on statistical learning in spatial navigation and memory consolidation. *Neuropsychologia, 174*, 108341. doi:https://doi.org/10.1016/j.neuropsychologia.2022.108341

Griffiths, T. L., & Tenenbaum, J. B. (2006). Optimal predictions in everyday cognition. *Psychological Science, 17*(9), 767-773. doi:https://doi.org/10.1111/j.1467-9280.2006.01780.x

Gruppelaar, V., Paassen, R. v., Mulder, M., & Abbink, D. (2018, 7-10 Oct. 2018). *A Perceptually Inspired Driver Model for Speed Control in Curves.* Paper presented at the 2018 IEEE International Conference on Systems, Man, and Cybernetics (SMC).

Hallmark, S., Oneyear, N., Wang, B., Tyner, S., Carney, C., & McGehee, D. (2015). *Identifying Curve Reaction Point Using NDS Data.* Paper presented at the IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC.

Harms, I. M., Burdett, B. R. D., & Charlton, S. G. (2021). The role of route familiarity in traffic participants' behaviour and transport psychology research: A systematic review. *Transportation Research Interdisciplinary Perspectives, 9*, 100331. doi:https://doi.org/10.1016/j.trip.2021.100331

Harms, I. M., van Dijken, J. H., Brookhuis, K. A., & de Waard, D. (2019). Walking Without Awareness. *Frontiers in Psychology, 10*(1846). doi:https://doi.org/10.3389/fpsyg.2019.01846

Hart, S. G. (2006). *NASA-task load index (NASA-TLX); 20 years later.* Paper presented at the Proceedings of the Human Factors and Ergonomics Society.

Hashim, I. H. (2011). Analysis of speed characteristics for rural two-lane roads: A field study from Minoufiya Governorate, Egypt. *Ain Shams Engineering Journal, 2*(1), 43-52. doi:https://doi.org/10.1016/j.asej.2011.05.005

Hashim, I. H., Abdel-Wahed, T. A., & Moustafa, Y. (2016). Toward an operating speed profile model for rural two-lane roads in Egypt. *Journal of Traffic and Transportation Engineering (English Edition), 3*(1), 82-88. doi:https://doi.org/10.1016/j.jtte.2015.09.005

Hassan, Y. (2004). Highway design consistency: Refining the state of knowledge and practice. *Transportation Research Record*(1881), 63-71. doi:https://doi.org/10.3141/1881-08

Hassan, Y., Sarhan, M., & Dimaiuta, M. (2011). Deficiencies in Existing Speed Models. In *Modeling Operating Speed: Synthesis Report*. Washington, D.C.: Transportation Research Board.

Hassan, Y., Sarhan, M., Porter, R., Dimaiuta, M., Donnell, E., Garcia, A., . . . Taylor, M. (2011). *Modeling Operating Speed: Synthesis Report*. Washington, D.C.: Transportation Research Board.

Hazenberg, S. J., & van Lier, R. (2016). Disentangling effects of structure and knowledge in perceiving partly occluded shapes: An ERP study. *Vision Research, 126*, 109-119. doi:https://doi.org/10.1016/j.visres.2015.10.004

Hills, B. L. (1980). Vision, Visibility, and Perception in Driving. *Perception, 9*(2), 183-216. doi:https://doi.org/10.1068/p090183

Himes, S., Porter, R. J., Hamilton, I., & Donnell, E. (2019). Safety Evaluation of Geometric Design Criteria: Horizontal Curve Radius and Side Friction Demand on Rural, Two-Lane Highways. *Transportation Research Record, 2673*, 516-525. doi:https://doi.org/10.1177/0361198119835514

Hughes, J., & Parkes, S. (2003). Trends in the use of verbal protocol analysis in software engineering research. *Behaviour and Information Technology, 22*(2), 127-140. doi:https://doi.org/10.1080/0144929031000081341

Jamson, S., Benetou, D., & Tate, F. (2015). The impact of arc visibility on curve negotiation. *Advances in Transportation Studies, 2015*(37), 79-92.

Kahneman, D. (2011). *Thinking, fast and slow*. New York: Farrar, Straus and Giroux.

Kanellaidis, G. (1995). Factors affecting drivers' choice of speed on roadway curves. *Journal of Safety Research, 26*(1), 49–56.

Kazemzadehazad, S., Monajjem, S., Larue, G. S., & King, M. J. (2019). Evaluating new treatments for improving driver performance on combined horizontal and crest vertical curves on two-lane rural roads: A driving simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour, 62*, 727-739. doi:https://doi.org/10.1016/j.trf.2019.03.002

Kim, S., & Choi, J. (2013). Effects of preceding geometric conditions on operating speed consistency of multilane highways. *Canadian Journal of Civil Engineering, 40*(6), 528-536. doi:https://doi.org/10.1139/cjce-2012-0051

Kircher, K., & Ahlstrom, C. (2018). Evaluation of methods for the assessment of attention while driving. *Accident Analysis & Prevention, 114*, 40-47. doi:https://doi.org/10.1016/j.aap.2017.03.013

Koiter, J. R. (2006). Visualizing inference in Bayesian networks. *Delft University of Technology, 855*.

Lamm, R., Choueiri, E. M., Hayward, J. C., & Paluri, A. (1988). Possible design procedure to promote design consistency in highway geometric design on two-lane rural roads. *Transportation Research Record, 1195*, 111.

Lamme, V. A. F. (2018). Challenges for theories of consciousness: Seeing or knowing, the missing ingredient and how to deal with panpsychism. *Philosophical Transactions of the Royal Society B: Biological Sciences, 373*(1755). doi:https://doi.org/10.1098/rstb.2017.0344

Land, M. F., & Lee, D. N. (1994). Where we look when we steer. *Nature, 369*(6483), 742-744. doi:https://doi.org/10.1038/369742a0

Lappi, O. (2014). Future path and tangent point models in the visual control of locomotion in curve driving. *Journal of Vision, 14*(12). doi:https://doi.org/10.1167/14.12.21

Lappi, O. (2022). Gaze strategies in driving–An ecological approach. *Frontiers in Psychology, 13*.

Lappi, O., & Lehtonen, E. (2012). *Tangent point orientation and anticipated trajectory curvature–a field study on the visual control of high speed steering.* Paper presented at the Annual Meeting of the Cognitive Science Society.

Lappi, O., & Lehtonen, E. (2013). Eye-movements in real curve driving: pursuit-like optokinesis in vehicle frame of reference, stability in an allocentric reference coordinate system. *Journal of Eye Movement Research, 6*(1), 1-13.

Lehtonen, E., Lappi, O., Koirikivi, I., & Summala, H. (2014). Effect of driving experience on anticipatory look-ahead fixations in real curve driving. *Accident Analysis & Prevention, 70*, 195-208. doi:https://doi.org/10.1016/j.aap.2014.04.002

Lehtonen, E., Lappi, O., Koskiahde, N., Mansikka, T., Hietamäki, J., & Summala, H. (2018). Gaze doesn't always lead steering. *Accident Analysis and Prevention, 121*, 268-278. doi:https://doi.org/10.1016/j.aap.2018.09.026

Lehtonen, E., Lappi, O., Kotkanen, H., & Summala, H. (2013). Look-ahead fixations in curve driving. *Ergonomics, 56*(1), 34-44. doi:https://doi.org/10.1080/00140139.2012.739205

Lehtonen, E., Lappi, O., & Summala, H. (2012). Anticipatory eye movements when approaching a curve on a rural road depend on working memory load. *Transportation Research Part F: Traffic Psychology and Behaviour, 15*(3), 369-377. doi:https://doi.org/10.1016/j.trf.2011.08.007

Lenne, M. G., Salmon, P. M., & Young, K. L. (2011). *An exploratory study assessing driver behaviour at highway-rail grade crossing using on-road test vehicles.* Paper presented at the 3rd International Conference on Road Safety and Simulation.

Li, P., & He, J. (2016). Geometric design safety estimation based on tire-road side friction. *Transportation Research Part C: Emerging Technologies, 63*, 114-125. doi:https://doi.org/10.1016/j.trc.2015.12.009

Llopis-Castelló, D., González-Hernández, B., Pérez-Zuriaga, A. M., & García, A. (2018) Speed Prediction Models for Trucks on Horizontal Curves of Two-Lane Rural Roads. In*: Vol. 2672. Transportation Research Record* (pp. 72-82).

Luque, R., & Castro, M. (2016). Highway Geometric Design Consistency: Speed Models and Local or Global Assessment. *International Journal of Civil Engineering, 14*(6), 347-355. doi:https://doi.org/10.1007/s40999-016-0025-2

Macuga, K. L. (2019). Multisensory Influences on Driver Steering During Curve Navigation. *Human Factors, 61*(2), 337-347. doi:https://doi.org/10.1177/0018720818805898

Mahapatra, G., & Kumar, A. M. (2018). Defining driving behaviour using friction-circle concept: An experimental study. *European Transport - Trasporti Europei*(67).

Malaghan, V., Pawar, D. S., & Dia, H. (2020). Modeling Operating Speed Using Continuous Speed Profiles on Two-Lane Rural Highways in India. *Journal of Transportation Engineering Part A: Systems, 146*(11). doi:https://doi.org/10.1061/JTEPBS.0000447

Malaghan, V., Pawar, D. S., & Dia, H. (2021). Modeling Acceleration and Deceleration Rates for Two-Lane Rural Highways Using Global Positioning System Data. *Journal of Advanced Transportation, 2021*. doi:https://doi.org/10.1155/2021/6630876

Malhotra, N., Charlton, S., Starkey, N., & Masters, R. (2018). Driving speed choice: The role of conscious monitoring and control (reinvestment) when driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 57*, 115-128. doi:https://doi.org/10.1016/j.trf.2017.06.006

Markkula, G., Lin, Y.-S., Srinivasan, A. R., Billington, J., Leonetti, M., Kalantari, A. H., . . . Merat, N. (2023). Explaining human interactions on the road by large-scale integration of computational psychological theory. *PNAS Nexus, 2*(6). doi:https://doi.org/10.1093/pnasnexus/pgad163

Martens, M., Comte, S., & Kaptein, N. (1997). *The effects of road design on speed behaviour: a literature review*.

Martens, M. H. (2018). The failure to respond to changes in the road environment: Does road familiarity play a role? *Transportation Research Part F: Traffic Psychology and Behaviour, 57*, 23-35. doi:https://doi.org/10.1016/j.trf.2017.08.003

McKnight, A. J., & Adams, B. B. (1970). *Driver education task analysis. Volume I: task descriptions. Final report*.

Mennie, N., Hayhoe, M., & Sullivan, B. (2007). Look-ahead fixations: Anticipatory eye movements in natural tasks. *Experimental Brain Research, 179*(3), 427-442. doi:https://doi.org/10.1007/s00221-006-0804-0

Michon, J. A. (1985). A Critical View of Driver Behavior Models: What Do We Know, What Should We Do? In L. Evans & R. C. Schwing (Eds.), *Human Behavior and Traffic Safety* (pp. 485-524). Boston, MA: Springer US.

Misaghi, P., & Hassan, Y. (2005). Modeling operating speed and speed differential on two-lane rural roads. *Journal of Transportation Engineering, 131*(6), 408-418. doi:https://doi.org/10.1061/(ASCE)0733-947X(2005)131:6(408)

Mole, C., Pekkanen, J., Sheppard, W. E. A., Markkula, G., & Wilkie, R. M. (2021). Drivers use active gaze to monitor waypoints during automated driving. *Scientific Reports, 11*(1). doi:https://doi.org/10.1038/s41598-020-80126-2

Molino, J. A., Opiela, K. S., Katz, B. J., & Moyer, M. J. (2005). Validate First; Simulate Later: A New Approach Used at the FHWA Highway Driving Simulator. *North America*, 10.

Montella, A., Galante, F., Imbriani, L. L., Mauriello, F., & Pernetti, M. (2014). Simulator evaluation of drivers' behaviour on horizontal curves of two-lane rural highways. *Advances in Transportation Studies*(34), 91-104.

Montella, A., Galante, F., Mauriello, F., & Aria, M. (2015). Continuous Speed Profiles to Investigate Drivers' Behavior on Two-Lane Rural Highways. *Transportation Research Record, 2521*(1), 3-11.

Montella, A., Galante, F., Mauriello, F., & Pariota, L. (2015) Low-cost measures for reducing speeds at curves on two-lane rural highways. In*: Vol. 2472. Transportation Research Record* (pp. 142-154).

Montella, A., Pariota, L., Galante, F., Imbriani, L. L., & Mauriello, F. (2014) Prediction of drivers' speed behavior on rural motorways based on an instrumented vehicle study. In*: Vol. 2434. Transportation Research Record* (pp. 52-62).

Nama, S., Sil, G., Maurya, A. K., & Maji, A. (2020) Acceleration and Deceleration Behavior in Departing and Approaching Sections of Curve Using Naturalistic Driving Data. In*: Vol. 69. Lecture Notes in Civil Engineering* (pp. 693-704).

Nationaal Dataportaal Wegverkeer. (2020). Retrieved from: https://www.ndw.nu/

Neisser, U. (1976). *Cognition and reality: Principles and implications of cognitive psychology*. New York, NY, US: W H Freeman/Times Books/ Henry Holt & Co.

Neumann, H., & Deml, B. (2011, 2011//). *The Two-Point Visual Control Model of Steering - New Empirical Evidence.* Paper presented at the Digital Human Modeling, Berlin, Heidelberg.

Odhams, A. M., & Cole, D. J. (2004, 2004). *Models of driver speed choice in curves.* Paper presented at the AVEC '04.

Othman, S., Thomson, R., & Lannér, G. (2009). *Identifying critical road geometry parameters affecting crash rate and crash type.* Paper presented at the Annals of advances in automotive medicine/annual scientific conference.

Othman, S., Thomson, R., & Lannér, G. (2010). Are driving and overtaking on right curves more dangerous than on left curves? *Annals of Advances in Automotive Medicine - 54th Annual Scientific Conference*, 253-264. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-78650866466&partnerID=40&md5=f5478de5a48e0dc3f052cb3969ba1a75

Pacejka, H., & Besselink, I. J. M. (2012). *Tire and Vehicle Dynamics*: Elsevier Science & Technology.

Pearl, J. (1988). *Probabilistic reasoning in intelligent systems*: Elsevier.

Peng, J., Chu, L., Wang, T., & Fwa, T. F. (2021). Analysis of vehicle skidding potential on horizontal curves. *Accident Analysis and Prevention, 152*. doi:https://doi.org/10.1016/j.aap.2020.105960

Perco, P. (2006). Desirable Length of Spiral Curves for Two-Lane Rural Roads. *Transportation Research Record: Journal of the Transportation Research Board, 1961*, 1-8. doi:https://doi.org/10.3141/1961-01

PIARC. (2016). *Human Factors Guidelines for a Safer Man-Road Interface*: PIARC - World Road Association.

Plant, K. L., & Stanton, N. A. (2012). Why did the pilots shut down the wrong engine? Explaining errors in context using Schema Theory and the Perceptual Cycle Model. *Safety Science, 50*(2), 300-315. doi:https://doi.org/10.1016/j.ssci.2011.09.005

Plant, K. L., & Stanton, N. A. (2013). The explanatory power of Schema Theory: theoretical foundations and future applications in Ergonomics. *Ergonomics, 56*(1), 1-15. doi:https://doi.org/10.1080/00140139.2012.736542

A Policy on Geometric Design of Highways and Streets 2018. (2018). Washington, D.C.: AASHTO.

Porter, R., Donnell, E., & Mason, J. (2012) Geometric design, speed, and safety. In. *Transportation Research Record* (pp. 39-47).

Pratt, M. P., Geedipally, S. R., Dadashova, B., Wu, L., & Shirazi, M. (2019) Familiar versus Unfamiliar Drivers on Curves: Naturalistic Data Study. In*: Vol. 2673. Transportation Research Record* (pp. 225-235).

Proctor, R. W., & Zandt, T. v. (2008). *Human Factors in simple and complex systems*. Boca Raton: Taylor & Francis Group.

Prokop, M., Pilař, L., & Tichá, I. (2020). Impact of Think-Aloud on Eye-Tracking: A Comparison of Concurrent and Retrospective Think-Aloud for Research on Decision-Making in the Game Environment. *Sensors, 20*(10), 2750. Retrieved from https://www.mdpi.com/1424-8220/20/10/2750

Ramsay, J. O., Hooker, G., & Graves, S. (2009). *Functional Data Analysis with R and MATLAB*. New York: Springer-Verlag.

Ranney, T. A. (1994). Models of driving behavior: A review of their evolution. *Accident Analysis & Prevention, 26*(6), 733-750. doi:https://doi.org/10.1016/0001-4575(94)90051-5

Rasmussen, J. (1982). Human errors. A taxonomy for describing human malfunction in industrial installations. *Journal of Occupational Accidents, 4*(2-4), 311-333. doi:https://doi.org/10.1016/0376-6349(82)90041-4

Rasmussen, J. (1983). Skills, rules, and knowledge; signals, signs, and symbols, and other distinctions in human performance models. *IEEE Transactions on Systems, Man, and Cybernetics, SMC-13*(3), 257-266. doi:https://doi.org/10.1109/TSMC.1983.6313160

Read, G., Beanland, V., Lenné, M., Stanton, N., & Salmon, P. (2017). *Integrating Human Factors Methods and Systems Thinking for Transport Analysis and Design*. Taylor & Francis Group, 6000 Broken Sound Parkway NW, Suite 300, Boca Raton, FL 33487-2742: CRC Press.

Reason, J. (1990). *Human error*: Cambridge university press.

Reymond, G., Kemeny, A., Droulez, J., & Berthoz, A. (2001). Role of lateral acceleration in curve driving: Driver model and experiments on a real vehicle and a driving simulator. *Human Factors, 43*(3), 483-495.

Richard, C. M., & Lichty, M. G. (2013). *Driver Expectations When Navigating Complex Interchanges* (FHWA-HRT-13-048). Retrieved from Georgetown Pike:

Riemersma, J. B. J. (1988). *The Perception of Curve Characteristics*. Soesterberg: Instituut voor Zintuigfysiologie.

Riemersma, J. B. J. (1989). *The effects of transition curves and superelevation on the perception of road-curve characteristics.*: Soesterberg, Institute for Perception.

Rijkswaterstaat. (2022). *ROA - Design Standards for Motorways 2019*. Utrecht: Rijkswaterstaat - Grote Projecten en Onderhoud

ROA - Knooppunten en Aansluitingen. (1993). (Vol. IV). Rotterdam: Rijkswaterstaat - Adviesdienst Verkeer en Vervoer.

Road Infrastructure Safety Management, 2008/96/EC, European Parliament and the Council of the European Union (2008).

Rogers, B. (2021). Optic Flow: Perceiving and Acting in a 3-D World. *i-Perception, 12*(1), 2041669520987257. doi:https://doi.org/10.1177/2041669520987257

Rolls, E. T. (2011). Consciousness, Decision-Making and Neural Computation. In V. Cutsuridis, A. Hussain, & J. G. Taylor (Eds.), *Perception-Action Cycle: Models, Architectures, and Hardware* (pp. 287 - 334). New York, NY: Springer New York.

Rumar, K. (1982). *Human factor in road safety*: Statens Väg-och Trafikinstitut. VTI Särtryck 81.

Russo, F., Biancardo, S. A., & Busiello, M. (2016). Operating speed as a key factor in studying the driver behaviour in a rural context. *Transport, 31*(2), 260-270. doi:https://doi.org/10.3846/16484142.2016.1193054

Ryan, A., Hennessy, E., Ai, C., Kwon, W., Fitzpatrick, C., & Knodler, M. (2022). Driver performance at horizontal curves: bridging critical research gaps to increase safety. *Traffic Safety Research, 3*, 000014. doi:https://doi.org/10.55329/lmji8901

Salmon, P. M., Goode, N., Spiertz, A., Thomas, M., Grant, E., & Clacy, A. (2017). Is it really good to talk? Testing the impact of providing concurrent verbal protocols on driving performance. *Ergonomics, 60*(6), 770-779. doi:10.1080/00140139.2016.1214752

Salmon, P. M., Lenne, M. G., Walker, G. H., Stanton, N. A., & Filtness, A. (2014). Exploring schema-driven differences in situation awareness between road users: An on-road study of driver, cyclist and motorcyclist situation awareness. *Ergonomics, 57*(2), 191-209. doi:https://doi.org/10.1080/00140139.2013.867077

Saltikoff, E., Friedrich, K., Soderholm, J., Lengfeld, K., Nelson, B., Becker, A., . . . Tassone, C. (2019). An Overview of Using Weather Radar for Climatological Studies: Successes, Challenges, and Potential. *Bulletin of the American Meteorological Society, 100*(9), 1739-1752. doi:https://doi.org/10.1175/bams-d-18-0166.1

Salvucci, D. D. (2006). Modeling driver behavior in a cognitive architecture. *Human Factors, 48*(2), 362–380.

Salvucci, D. D., & Gray, R. (2004). A Two-Point Visual Control Model of Steering. *Perception, 33*(10), 1233-1248. doi:https://doi.org/10.1068/p5343

Schipperijn, J., Kerr, J., Duncan, S., Madsen, T., Klinker, C. D., & Troelsen, J. (2014). Dynamic accuracy of GPS receivers for use in health research: A novel method to assess GPS accuracy in real-world settings. *Frontiers in Public Health, 2*(MAR). doi:https://doi.org/10.3389/fpubh.2014.00021

Schubert, M. C., Migliaccio, A. A., & Della Santina, C. C. (2006). Dynamic Visual Acuity during Passive Head Thrusts in Canal Planes. *Journal of the Association for Research in Otolaryngology, 7*(4), 329-338. doi:https://doi.org/10.1007/s10162-006-0047-6

Seriès, P., & Seitz, A. R. (2013). Learning what to expect (in visual perception). *Frontiers in Human Neuroscience, 7*. doi:https://doi.org/10.3389/fnhum.2013.00668

Shalkamy, A., Gargoum, S., & El-Basyouny, K. (2021). Towards a more inclusive and safe design of horizontal curves: Exploring the association between curve features, reliability measures, and safety. *Accident Analysis and Prevention, 153*. doi:https://doi.org/10.1016/j.aap.2021.106009

Shallam, R. D. K., & Ahmed, M. A. (2016). Operating Speed Models on Horizontal Curves for Two-lane Highways. *Transportation Research Procedia, 17*, 445-451. doi:https://doi.org/10.1016/j.trpro.2016.11.086

Sherman, B. E., Graves, K. N., & Turk-Browne, N. B. (2020). The prevalence and importance of statistical learning in human cognition and behavior. *Current Opinion in Behavioral Sciences, 32*, 15-20. doi:https://doi.org/10.1016/j.cobeha.2020.01.015

Shinar, D. (2017a). 2. Research Methods. In *Traffic Safety and Human Behavior (2nd Edition)*: Emerald, Inc.

Shinar, D. (2017b). 3. Theories and Models of Driver Behavior. In *Traffic Safety and Human Behavior (2nd Edition)*: Emerald, Inc.

Shinar, D. (2017c). 5. Driver Information Processing: Attention, Perception, Reaction Time, and Comprehension. In *Traffic Safety and Human Behavior (2nd Edition)*: Emerald, Inc.

Shinar, D. (2017d). 8. Speed and Safety. In *Traffic Safety and Human Behavior (2nd Edition)*: Emerald, Inc.

Shinar, D., McDowell, E. D., & Rockwell, T. H. (1977). Eye movements in curve negotiation. *Human Factors, 19*(1), 63–71.

Singh, M., & Fulvio, J. M. (2007). Bayesian contour extrapolation: Geometric determinants of good continuation. *Vision Research, 47*(6), 783-798. doi:https://doi.org/10.1016/j.visres.2006.11.022

Sitran, A., Delhaye, E., & Uccelli, I. (2016). Directive 2008/96/EC On Road Infrastructure Safety Management: An Ex-post Assessment 5 years After its Adoption. *Transportation Research Procedia, 14*, 3312-3321. doi:https://doi.org/10.1016/j.trpro.2016.05.279

Sivak, M. (1996). The Information That Drivers Use: Is it Indeed 90% Visual? *Perception, 25*(9), 1081-1089. doi:https://doi.org/10.1068/p251081

Spering, M., & Carrasco, M. (2015). Acting without seeing: eye movements reveal visual processing without awareness. *Trends in Neurosciences, 38*(4), 247-258. doi:https://doi.org/10.1016/j.tins.2015.02.002

Springer, J. F., & Huizenga, K. E. (1975). *The Road-Picture as a Touchstone for the Threedimensional Design of Roads*. (20). The Hague: Government Publishing Office

Springer, J. F., Huizenga, K. E., & Moonen, A. M. (1970). Beschouwingen ten aanzien van een esthetisch verantwoorde vormgeving van de wegen (III). *Wegen, 651*, 43-49.

Stanton, N. A., & Salmon, P. M. (2009). Human error taxonomies applied to driving: A generic driver error taxonomy and its implications for intelligent transport systems. *Safety Science, 47*(2), 227-237. doi:https://doi.org/10.1016/j.ssci.2008.03.006

Stapel, J., El Hassnaoui, M., & Happee, R. (2020). Measuring Driver Perception: Combining Eye-Tracking and Automated Road Scene Perception. *Human Factors*, 0018720820959958. doi:https://doi.org/10.1177/0018720820959958

Sullivan, B., Ludwig, C. J. H., Damen, D., Mayol-Cuevas, W., & Gilchrist, I. D. (2021). Look-ahead fixations during visuomotor behavior: Evidence from assembling a camping tent. *Journal of Vision, 21*(3), 1-17. doi:https://doi.org/10.1167/jov.21.3.13

Summala, H. (2007). Towards Understanding Motivational and Emotional Factors in Driver Behaviour: Comfort Through Satisficing. In P. C. Cacciabue (Ed.), *Modelling Driver Behaviour in Automotive Environments: Critical Issues in Driver Interactions with Intelligent Transport Systems* (pp. 189-207). London: Springer London.

SWOV. (2018). *Sustainable Safety 3rd edition – The advanced vision for 2018-2030; Principles for design and organization of a casualty-free road traffic system* (978-90-73946-17-0). Retrieved from The Hague:

Tenenbaum, G., & Filho, E. (2016). Chapter 3 - Measurement Considerations in Performance Psychology. In M. Raab, B. Lobinger, S. Hoffmann, A. Pizzera, & S. Laborde (Eds.), *Performance Psychology* (pp. 31-44). San Diego: Academic Press.

Tenenbaum, J. B., Kemp, C., Griffiths, T. L., & Goodman, N. D. (2011). How to grow a mind: Statistics, structure, and abstraction. *Science, 331*(6022), 1279-1285. doi:https://doi.org/10.1126/science.1192788

Theeuwes, J. (2021). Self-explaining roads: What does visual cognition tell us about designing safer roads? *Cognitive Research: Principles and Implications, 6*(1), 15. doi:https://doi.org/10.1186/s41235-021-00281-6

Theeuwes, J., & Godthelp, H. (1995). Self-explaining roads. *Safety Science, 19*(2-3), 217-225. doi:https://doi.org/10.1016/0925-7535(94)00022-U

Theeuwes, J., Horst, R. v. d., & Kuiken, M. (2012). *Designing safe road systems: a human factors perspective*. Farnham, Surrey, England ; Burlington, VT: Ashgate.

Thomas, M., Goode, N., Grant, E., Taylor, N. Z., & Salmon, P. M. (2015). Can we talk about Speed? The Effect of Verbal Protocols on Driver Speed and Perceived Workload. *Procedia Manufacturing, 3*, 2629-2634. doi:https://doi.org/10.1016/j.promfg.2015.07.608

Tobii Pro, A. (2021). Tobii Pro Lab (Version 1.181.37603 (x64)): Tobii Pro, AB. Retrieved from https://www.tobiipro.com/

Torbic, D. J., Donnell, E. T., Brennan, S. N., Brown, A., O'Laughlin, M. K., & Bauer, K. M. (2014) Superelevation design for sharp horizontal curves on steep grades. In*: Vol. 2436. Transportation Research Record* (pp. 81-91).

Transport and mobility 2016. (2016). (S. Netherlands Ed.). The Hague: Statistics Netherlands.

Tuhkanen, S., Pekkanen, J., Rinkkala, P., Mole, C., Wilkie, R. M., & Lappi, O. (2019). Humans Use Predictive Gaze Strategies to Target Waypoints for Steering. *Scientific Reports, 9*(1). doi:https://doi.org/10.1038/s41598-019-44723-0

Van Hasselt, C. M. (2009). CycloMedia technology: BV visualisation and beyond. *GIM International, 23*(11), 40-41.

Van Winsum, W., & Godthelp, H. (1996). Speed choice and steering behavior in curve driving. *Human Factors, 38*(3), 434-441. doi:https://doi.org/10.1518/001872096778701926

Vos, J. (2022). *Speed Behaviour and Traffic Safety in Connector Roads Second Curves*. Paper presented at the International Symposium on Highway Geometric Design, Amsterdam.

Vos, J., de Winter, J., Farah, H., & Hagenzieker, M. (2023). Which visual cues do drivers use to anticipate and slow down in freeway curve approach? An eye-tracking, think-aloud on-road study. *Transportation Research Part F: Traffic Psychology and Behaviour, 94*, 190-211. doi:https://doi.org/10.1016/j.trf.2023.01.021

Vos, J., & Farah, H. (2022). Speed development at freeway curves based on high frequency floating car data. *European Journal of Transport and Infrastructure Research, 22*(2), 201-223. doi:https://doi.org/10.18757/ejtir.2022.22.2.6114

Vos, J., Farah, H., & Hagenzieker, M. (2021a). How do dutch drivers perceive horizontal curves on freeway interchanges and which cues influence their speed choice? *IATSS Research, 45*(2), 258-266. doi:https://doi.org/10.1016/j.iatssr.2020.11.004

Vos, J., Farah, H., & Hagenzieker, M. (2021b). Speed behaviour upon approaching freeway curves. *Accident Analysis & Prevention, 159*, 106276. doi:https://doi.org/10.1016/j.aap.2021.106276

Wagemans, J., Feldman, J., Gepshtein, S., Kimchi, R., Pomerantz, J. R., van der Helm, P. A., & van Leeuwen, C. (2012). A century of Gestalt psychology in visual perception: II. Conceptual and theoretical foundations. *Psychological Bulletin, 138*(6), 1218-1252. doi:https://doi.org/10.1037/a0029334

Walker, G. H., Stanton, N. A., & Chowdhury, I. (2013). Self Explaining Roads and situation awareness. *Safety Science, 56*, 18-28. doi:https://doi.org/10.1016/j.ssci.2012.06.018

Walker, G. H., Stanton, N. A., & Salmon, P. M. (2011). Cognitive compatibility of motorcyclists and car drivers. *Accident Analysis and Prevention, 43*(3), 878-888. doi:https://doi.org/10.1016/j.aap.2010.11.008

Wang, F., & Easa, S. M. (2009). Validation of perspective-view concept for estimating road horizontal curvature. *Journal of Transportation Engineering, 135*(2), 74-80.

Wang, X., Guo, Q., & Tarko, A. P. (2020). Modeling speed profiles on mountainous freeways using high resolution data. *Transportation Research Part C: Emerging Technologies, 117*. doi:https://doi.org/10.1016/j.trc.2020.102679

Wegman, F. (2017). The future of road safety: A worldwide perspective. *IATSS Research, 40*(2), 66-71. doi:https://doi.org/10.1016/j.iatssr.2016.05.003

Wet van 2 december 2010 tot aanpassing van de Wet beheer rijkswaterstaatswerken ter implementatie van richtlijn 2008/96/EG van het Europees Parlement en de Raad van 19 november 2008 betreffende het beheer van de verkeersveiligheid van weginfrastructuur, PbEU L 319/59 (2010).

Wickens, C. D., Helton, W. S., Hollands, J. G., & Banbury, S. (2021). *Engineering psychology and human performance*: Routledge.

Wilde, G. J. (1998). Risk homeostasis theory: an overview. *Injury prevention, 4*(2), 89-91.

Wilder, J., Feldman, J., & Singh, M. (2016). The role of shape complexity in the detection of closed contours. *Vision Research, 126*, 220-231. doi:https://doi.org/10.1016/j.visres.2015.10.011

Windey, B., Vermeiren, A., Atas, A., & Cleeremans, A. (2014). The graded and dichotomous nature of visual awareness. *Philosophical transactions of the Royal Society of London. Series B, Biological sciences, 369*(1641), 20130282-20130282. doi:https://doi.org/10.1098/rstb.2013.0282

Wolfe, B., Sawyer, B. D., & Rosenholtz, R. (2022). Toward a Theory of Visual Information Acquisition in Driving. *Human Factors, 64*(4), 694-713. doi:https://doi.org/10.1177/0018720820939693

Wu, J., & Xu, H. (2018). The influence of road familiarity on distracted driving activities and driving operation using naturalistic driving study data. *Transportation Research Part F: Traffic Psychology and Behaviour, 52*, 75-85. doi:https://doi.org/10.1016/j.trf.2017.11.018

Xie, L., Wu, C., Lyu, N., & Duan, Z. (2019). Studying the effects of freeway alignment, traffic flow, and sign information on subjective driving workload and performance. *Advances in Mechanical Engineering, 11*(5), 1687814019853690. doi:https://doi.org/10.1177/1687814019853925

Young, A. H., Mackenzie, A. K., Davies, R. L., & Crundall, D. (2018). Familiarity breeds contempt for the road ahead: The real-world effects of route repetition on visual attention in an expert driver. *Transportation Research Part F: Traffic Psychology and Behaviour, 57*, 4-9. doi:https://doi.org/10.1016/j.trf.2017.10.004

Zegeer, C. V., Stewart, J. R., Council, F. M., & Reinhurt, D. (1991). Safety effects of geometric improvements on horizontal curves. *Transportation Research Record*(1356), p. 11-19.

About the Author

Johan Vos was born in Zwolle, the Netherlands in 1982. He obtained his bachelor's degree in Traffic Engineering at the Noordelijke Hogeschool Leeuwarden in 2003. His bachelors group-project "De Nieuwe Verbinding" employed a design process which identified topographical constraints to create possible alignment corridors for a new road, and won the "Vitae Civiel Award" as the best Dutch Civil Engineering Bachelors graduation.

After this he continued on the Rijksuniversiteit Groningen to pursue a master's degree in Environmental and Infrastructure Planning. He obtained this master's degree in 2007 with a thesis called "Postmoderne interpretaties van militaire cultuurhistorie" ("Postmodern interpretations of military cultural heritage").

During his Master's program, he was board member of the Faculty Union of spatial sciences "Ibn Battuta" and started to work part-time as a traffic engineer at Arcadis. After he obtained his Master's degree, he started working full-time as a traffic engineer at Movares, where he, among other projects, worked on several freeway widening projects for Rijkswaterstaat. During this time he also got certified as an independent Road Safety Auditor as part of the European "Road Infrastructure Safety Management" program. To obtain further insights in human factors, he obtained two certificates in Cognitive Psychology at Utrecht University in 2014 ("Sensation and Perception" & "Applied Cognitive Psychology").

In 2016 Johan switched from industry to government and joined Rijkswaterstaat (executive agency of the Ministry of Infrastructure), where he still works. He is the editor of the Dutch geometric design guidelines for freeways, established guidelines for the road design process and heads the knowledge field of road design for Rijkswaterstaat.

In 2019 he started his part-time PhD research at Delft University of Technology, department of Transport and Planning, combining it with his job at Rijkswaterstaat to strengthen scientific backgrounds of geometric freeway design. During his PhD, he focussed on human factors and holistic freeway curve design. After his PhD, he will continue part-time work at the Traffic and Transport Safety Lab, aiming at applied research into geometric road design.

Publications

Vos, J., Farah, H., & Hagenzieker, M. (2021). How do dutch drivers perceive horizontal curves on freeway interchanges and which cues influence their speed choice? *IATSS Research*. doi:https://doi.org/10.1016/j.iatssr.2020.11.004

Vos, J., Farah, H., & Hagenzieker, M. (2021). Speed behaviour upon approaching freeway curves. *Accident Analysis & Prevention, 159*, 106276. doi:https://doi.org/10.1016/j.aap.2021.106276

Vos, J., & Farah, H. (2022). Speed development at freeway curves based on high frequency floating car data. *European Journal of Transport and Infrastructure Research, 22*(2), 201-223. doi:https://doi.org/10.18757/ejtir.2022.22.2.6114

Afghari, A. P., **Vos, J.**, Farah, H., & Papadimitriou, E. (2023). “I did not see that coming”: A latent variable structural equation model for understanding the effect of road predictability on crashes along horizontal curves. *Accident Analysis & Prevention, 187,* 107075. doi:https://doi.org/10.1016/j.aap.2023.107075

Vos, J., de Winter, J., Farah, H., & Hagenzieker, M. (2023). Which visual cues do drivers use to anticipate and slow down in freeway curve approach? An eye-tracking, think-aloud on-road study. *Transportation Research Part F: Traffic Psychology and Behaviour, 94*, 190-211. doi:https://doi.org/10.1016/j.trf.2023.01.021

Vos, J., Farah, H., & Hagenzieker, M. (under review). *Modelling Driver Expectations for Safe Speeds on Freeway Curves using Bayesian Belief Networks*

Presentations

Vos, J., & Farah, H. (2022). *Speed development at freeway curves based on high frequency floating car data.* Paper presented at the Transportation Research Board Annual Meeting, Washington DC.

Vos, J. (2022). *Speed Behaviour and Traffic Safety in Connector Roads Second Curves*. Paper presented at the International Symposium on Highway Geometric Design, Amsterdam.

Vos, J., Farah, H., & Hagenzieker, M. (2022). *How do dutch drivers perceive horizontal curves on freeway interchanges and which cues influence their speed choice?* Paper presented at the International Symposium on Highway Geometric Design, Amsterdam.

Afghari, A. P., **Vos, J.**, Farah, H., & Papadimitriou, E. (2023). *“I did not see that coming”: A latent variable structural equation model for understanding the effect of road predictability on crashes along horizontal curves.* Paper presented at the Transportation Research Board Annual Meeting, Washington DC.

Vos, J., de Winter, J., Farah, H., & Hagenzieker, M. (2023). *Which visual cues do drivers use to anticipate and slow down in freeway curve approach? An eye-tracking, think-aloud on-road study.* Paper presented at the Verkeersgedragdag, Rotterdam.

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Summary

This dissertation explores what road characteristics trigger drivers' speed adjustments when approaching freeway curves. It combines speed prediction modelling and human factors research methods. The results show that drivers primarily consider visible cues such as the preceding roadway, deflection angle, and the number of lanes, as opposed to traditional factors like horizontal radius or speed signs, when starting to decelerate. The study advocates for integrating driver perspectives into road design.

About the Author

Johan Vos is employed at Rijkswaterstaat, where he oversees Dutch freeway geometric design guidelines. Additionally, he conducts part-time applied research at Delft University of Technology's Transport and Planning department, with a focus on human factors and geometric freeway design.

TRAIL Research School ISBN 978-90-5584-340-4

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