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Expert Drivers' Prospective Thinking-Aloud to Enhance Automated Driving Technologies – Investigating Uncertainty and Anticipation in Traffic

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ABSTRACT

Current automated driving technology cannot cope in numerous conditions that are basic daily driving situations for human drivers. Previous studies show that profound understanding of human drivers' capability to interpret and anticipate traffic situations is required in order to provide similar capacities for automated driving technologies. There is currently not enough a priori understanding of these anticipatory capacities for safe driving applicable to any given driving situation. To enable the development of safer, more economical, and more comfortable automated driving experience, expert drivers' anticipations and related uncertainties were studied on public roads. First, driving instructors' expertise in anticipating traffic situations was validated with a hazard prediction test. Then, selected driving instructors drove in real traffic while thinking aloud anticipations of unfolding events. The results indicate sources of uncertainty and related adaptive and social behaviors in specific traffic situations and environments. In addition, the applicability of these anticipatory capabilities to current automated driving technology is discussed. The presented method and results can be utilized to enhance automated driving technologies by indicating their potential limitations and may enable improved situation awareness for automated vehicles. Furthermore, the produced data can be utilized for recognizing such upcoming situations, in which the human should take over the vehicle, to enable timely take-over requests.

Keywords

Automated driving; expert driver; prospective thinking-aloud; traffic safety; uncertainty; anticipation

1 INTRODUCTION

Automated driving solutions (i.e., autopilot technologies) are becoming increasingly common in commercial vehicles. The aim of automated driving technology is to substantially decrease accidents and increase driving comfort (Hubmann et al., 2018). Automated driving technologies are sometimes claimed to be safer than human drivers (e.g., McGoogan, 2016; Associated Press, 2018; Teoh & Kidd, 2017), and in many respects they may be superior to a human driver. They are able, for instance, to monitor surrounding objects continuously – automated driving technologies do not get tired or bored during monotonous driving as human drivers tend to do (Horne and Reyner, 1995; Schmidt et al., 2009; Thiffault and Bergeron, 2003; Ting et al., 2008).

One major manufacturer of automated driving technology is Tesla, Inc. and it has been estimated that Tesla's autopilot has driven over 2.2 billion miles on public roads by January 2020 (Friedman, 2020). Nonetheless, these successfully driven kilometers in limited driving scenarios may not be a sufficient indicator of the safety or superiority of these systems over human drivers – automated driving technologies still have some major weaknesses compared to human drivers. Up to now, little attention has been paid to these weaknesses and how human drivers manage in similar situations.

The current traffic system is a social environment where other road users' behavior determines how drivers interact with each other (Zaidel, 1992). Driving is not only a mechanical performance, it is also a "complex social activity" (Brown, 2017). Hence, the interaction between automated driving technology and other road users is gaining attention in the literature (e.g., Brown & Laurier, 2017; Rasouli & Tsotsos, 2019). Schwarting, Alonso-Mora, and Rus (2018) have stated that interaction between automated driving technologies and human road users is "an unsolved problem". Previous research has identified these problems that automated driving technologies might come across in traffic while interacting with humans – such as lack of negotiation with human drivers (Chater et al., 2018), social issues regarding lane changes and merging (Brown and Laurier, 2017), as well as lack of interaction and communication with pedestrians (Mahadevan et al., 2018). All these studies describing interaction problems between humans and automated driving technologies concluded that these technologies need more "human-like" features to overcome the found social issues.

What could these "human-like" features be? What could explain the insufficiencies of Tesla's autopilot and other self-driving cars compared to human drivers? Stahl, Donmez, and Jamieson (2013) suggested that we should better understand human drivers' capability to interpret and predict traffic situations to facilitate drivers' competence. Correspondingly, we suggest that one of these "human-like" features that state-of-the-art automated driving technologies lack is the skill of anticipation of traffic events, and more specifically, the skill of recognizing uncertainties concerning the unfolding driving situation and adapting to these accordingly. With this knowledge, automated driving technologies could be trained to perform in a similar way than humans do – or even better.

The aim of this paper is to investigate human experts' uncertainties that rise in anticipatory driving and their related adaptive behaviors. This knowledge is important in order to improve today's automated driving technologies to be safer, more economical, and more comfortable. The research questions are: 1) What are the context-dependent uncertainties that arise in anticipatory driving of expert drivers (here: driving instructors)? and 2) How expert drivers adapt their behavior in the identified driving situations in order to resolve the uncertainties?

First, commercial hazard perception test video clips were analyzed for identifying the situations which may be efficiently anticipated by human drivers but which could cause problems to current automated driving technologies for numerous reasons, such as poor visibility, objects that are partially occluded, unexpected trajectories, or lack of understanding the world. The selected video clips were transformed into hazard prediction clips by ending them with an occlusion just after the hazardous situation started to unfold. These hazard prediction clips were used to test if there are differences between inexperienced, a mixed group of drivers, and driving instructors in anticipating unfolding hazards in traffic. With this experiment, the selected driving instructors' expertise in hazard prediction ability was validated. After the expert sample validation, six of the experts drove a predefined route on public roads while thinking aloud prospectively what driving-task relevant they are anticipating to happen. The research process is illustrated in Figure 1. Based on the content analysis of the data, uncertainties, as well as related adaptive and social behaviors in specific traffic situations and environments, were identified. To our best knowledge, this paper is the first to investigate human expert drivers' anticipations and uncertainties on public roads with the prospective thinking-aloud method.

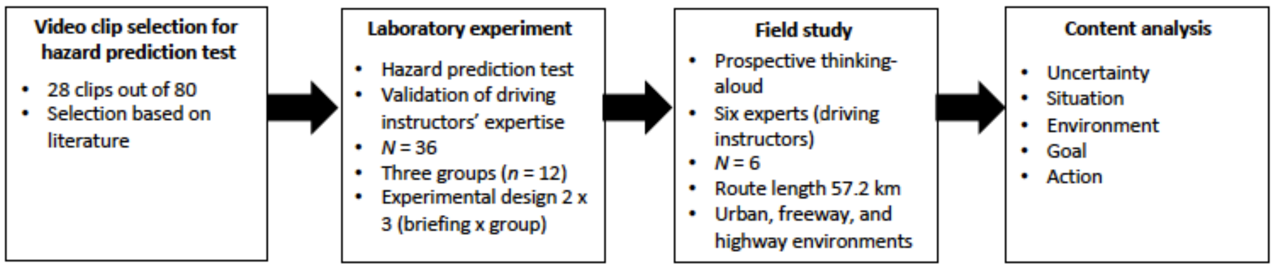

Figure 1: Research process

2 RELATED LITERATURE

2.1 Automated driving taxonomy and situation awareness

In order to provide understanding of current automated driving technologies and their abilities, the Society of Automotive Engineers (2019) has presented a taxonomy regarding levels of automated driving. Some of today's automated driving technologies may be classified at the third level: automated driving technology can drive the vehicle under limited conditions, and when the system requires, the driver must take over the automated driving technology (SAE, 2019). However, in order to succeed in safe driving already at these levels, the driving task requires situation awareness (Matthews et al., 2001; Ward, 2000).

According to Endsley (1995), situation awareness (SA) refers to understanding the environment's state for succeeding in a task. SA has three levels: perception of the elements in the environment (Level 1), comprehension of the current situation (Level 2), and projection of its future status (Level 3). All levels of driving task (operational, tactical, and strategic) require each level of situation awareness (Matthews et al., 2001).

It can be argued that today's automated driving technology may reach the Level 1 of situation awareness: they recognize environment's elements such as other vehicles, road curviness, and obstacles. But do automated driving technologies reach the Level 2 of situation awareness, comprehension of the current situation? According to Lake, Ullman, Tenenbaum, and Gershman (2017), automated driving technology algorithms can only recognize objects but cannot understand scenes, that is, *comprehend the current situation*.

Situation awareness' Level 3 requires anticipating the future status of the task environment. In the automotive context this means, for instance, predicting other road users' behavior. Predicting other road users' trajectories with different machine learning techniques is, indeed, a growing research area (e.g., lane changes: Chae, Lee, & Yi, 2017; Dong, Chen, & Dolan, 2019; Wissing, Nattermann, Glander, & Bertram, 2018). According to academic research, state-of-the-art automated driving algorithms may be able to predict trajectories of recognized moving objects when interacting with these objects, selecting optimal paths and speeds accordingly, for instance, in complex intersection scenarios (Hubmann et al., 2018). Meghjani et al. (2019) have developed decision-making algorithms that are able to utilize contextual information (e.g., map data of intersections and lanes ahead) in inferring intentions of the cars in front of the ego vehicle for optimizing lane changes and route planning under uncertainty. However, these fairly low-level and relatively short-term prediction abilities are not yet sufficient when compared to human expert drivers. Lake et al. (2017) point out that – compared to humans – automated driving technologies lack intuitive psychology to be able to anticipate other road users' behavior and intentions. Furthermore, they are lacking in intuitive physics in order to reason about the stability and trajectories of objects that may be occluded momentarily by other objects in the environment. That said, it could be argued that today’s autopilots have severe deficiencies at Levels 2 and 3 of situation awareness, which are crucial for safe and comfortable driving (e.g., Baumann & Krems, 2007; Stahl et al., 2013).

2.2 Problems current automated driving technologies encounter on public roads

The literature review on automated technology problems is focused on publications between 2015 and 2020 as the technology is developing rapidly. There are numerous of YouTube videos available where one can see situations in which the driver needs to overtake the automated driving technology (e.g., https://tinyurl.com/yywtj4oo and https://tinyurl.com/y3kae45d). In these videos, Tesla autopilot owners have recorded their drives on public roads while enabling the autopilot. Based on the real-life footage, human intervene is needed, for instance, in situations where lane markings are not clear, when road is too narrow, when ramp is too curvy, or when there are unusual objects on the road.

The lack of scene understanding and future status anticipation may be some of the reasons that have led automated driving technologies to encounter these problems on public roads. One additional component of scene understanding could be the understanding of the social side of traffic. Brown and Laurier (2017) analyzed YouTube video clips of self-driving cars recorded by drivers and documented social challenges that automated driving technologies confront in real traffic. They noticed, for instance, how automated driving technology’s lane-changing behavior can be interpreted as rude, how automated driving technology maintaining speed and following traffic lines in merging cause a hazardous situation, and when automated driving technology is not “creeping” in the four-way stop intersection it gets “cut-up” and causes sudden braking. All these actions risk safe, economical, and comfortable traffic flow.

Endsley (2017) studied (based on her own experiences) Tesla's autopilot for a six-month period in 2017. During the period, Tesla's autopilot had problems with sharp turns, curves, merging lanes, and intersections without lane markings. Similarly, Dikmen and Burns (2016) found out in their survey that Tesla's autopilot's lane detection failures caused problems to drivers: the autopilot tried to take an exit ramp and cross lanes for no reason, for example. Endsley (2017) also noticed that while parking, avoiding an obstacle on Tesla's way also led the autopilot into a strange turning angle in a tight place.

According to Dikmen and Burns (2016), one of the current automated driving technologies' major problems is sudden changes in speed. Sudden braking and uncomfortable accelerations and decelerations were brought up in the survey they conducted – these were problems especially in heavy traffic conditions. Naturally, even if not safety-critical, these sudden speed changes are diminishing driving comfort.

Lv et al. (2018) studied automated driving technology manufacturers' reports that summarize incidents when either the technology itself disengaged the autopilot, or the autopilot was disabled by the driver. The latter is called "active disengagement" and means that the automated driving technology does not detect any problem, but the driver notices some unfolding event that makes the driver to take over the control of the car. Active disengagements happened, for instance, when there were too many vehicles and other road users in an intersection; when the automated driving technology did not slow down when a vehicle in front stopped; when the automated driving technology did not recognize a vehicle pulling out from a parking lot; when there was an emergency vehicle on the road or an accident; when other drivers' behavior was unexpected or reckless; and when extra space for a cyclist was needed. All these examples can be considered as situations that diminish safe driving and causes uncertainty of the automated driving technologies' behavior for the driver or passengers.

The reasons causing drivers to disable the automated driving technology have also been studied in a driving simulator. van Huysduynen, Terken, and Eggen (2018) noticed in their driving simulator study that the automated driving technology was disabled, for instance, in situations where the technology was perceived as conservative. This means that it reduced speed before passing, and after passing it constantly tried to return to the right lane even if there were slower traffic ahead. Therefore, one recognized reason to disable the automated driving technology was to maintain the traffic flow when changing lanes. Another reason to disable the automated driving technology was due to unpredictability of other road users – drivers did not trust that the technology would cope in those situations. Again, maintaining the traffic flow and coping in uncertain situations are linked to safer, more economical, and more comfortable driving.

In addition, an increasing number of studies have investigated the interaction between automated driving technologies and pedestrians in urban environments. For example, Mahadevan et al. (2018) focused on communication and interaction between automated driving technologies and humans. They emphasized the importance of the communication that the vehicle is aware of pedestrians. This kind of interaction is easy for human drivers (e.g., Schneemann & Gohl, 2016), but the way how automated driving technologies could communicate their intentions to pedestrians still remains as a question. A number of studies have examined how this communication could be enabled by technical means (e.g., Ackermann, Beggiato, Schubert, & Krems, 2019; Chang, Toda, Sakamoto, & Igarashi, 2017; de Clercq, Dietrich, Núñez Velasco, de Winter, & Happee, 2019; Habibovic et al., 2018; Lee et al., 2019; Li, Dikmen, Hussein, Wang, & Burns, 2018; Mirnig, Perterer, Stollnberger, & Tscheligi, 2017). However, the communication should be efficient also to the other direction: the vehicle should be able to recognize the intentions of the pedestrians and other vulnerable road users (Rasouli and Tsotsos, 2019; Schwarting et al., 2019).

Based on the literature, problems automated driving technologies are encountering on roads are linked to safe, economical, and comfortable driving. Hence, what could be done to solve these problems?

2.3 Cognitive mimetics

Brown and Laurier (2017) as well as Chater et al. (2018) have concluded that human-computer interaction (HCI) and cognitive science could aid in designing better self-driving cars. One of the relevant paradigms could be cognitive mimetics (Kujala and Saariluoma, 2018; Saariluoma et al., 2018). This way of design thinking suggests that mimicking expert human drivers' information processing and thinking could be utilized for designing safer, more economical, and more comfortable automated driving technologies. The idea of design mimetics, that is, imitating physical and biological structures in nature for technology design, has been known since the fifties (Bar-Cohen, 2006). The core idea of cognitive mimetics is that instead of imitating these structures of nature, designers should focus on human experts' information processes and thinking when searching for model solutions (Kujala and Saariluoma, 2018; Saariluoma et al., 2018).

Thanks to its internal and information processing focus, cognitive mimetics differs from ethnographic approaches. Vinkhuyzen and Cefkin (2016), for example, studied how people behave in traffic and how this information could be utilized when developing and improving current automated driving technologies. They observed pedestrians and their behavior in order to teach automated driving technology to behave in "socially appropriate ways". However, in cognitive mimetics it is essential to pay attention also to the contents of experts' information processes (i.e., mental contents) (Newell and Simon, 1972). Recently, researchers in the field have started to realize the importance of examining human road users' behavior and its modeling in order to develop better automated driving technologies (e.g., Domeyer et al., 2019; Markkula et al., 2020, 2018; Merat et al., 2019). Due to the importance of anticipation of traffic events for successful driving (Stahl et al., 2013), the goal for investigating expert drivers' behavior here is to get a clearer idea of the information contents relevant in anticipatory driving.

2.4 Anticipatory driving and uncertainty

According to Pollatsek, Narayanaan, Pradhan, and Fisher (2006), novice drivers' fatality rate is eight times higher than the rate of highly experienced drivers. One causing factor is novice drivers' incapability to anticipate safety-relevant traffic events. Therefore, the anticipation of traffic situations is a critical component of driver competence, which allows drivers to maintain sufficient safety margins (Stahl et al., 2016). According to Tanida and Pöppel (2006), if the driving situation is perceived as familiar, drivers are able to anticipate what is going to happen next and to act accordingly. Conversely, if the driving situation is unfamiliar, drivers need to react to events. With human drivers, traffic flow, safety, and economical driving can be improved by moving from reactionary driving to anticipatory driving (Stahl et al., 2013).

Human experts' anticipatory skills (Clark, 2013) and the ability to focus processing situationally on task-relevant targets may be some of the key differences that separate human and machine intelligence. Based on neurological evidence, it has been proposed that the human brain is an advanced prediction machine (Clark, 2013). According to these accounts, its basic function is to continuously predict and anticipate the upcoming events and assess the uncertainty of the predictions. This framework of cognition stresses the importance of predictive uncertainty and its resolution in human attention allocation and behavior. In line with these ideas, it has been recently shown that experienced drivers' perceived uncertainty of upcoming traffic events on a freeway is a major factor in their visual information sampling (Kircher et al., 2019). In a similar vein, for instance, Meghjani et al. (2019) and Hubmann et al. (2018) stress the importance of modeling uncertainty in the development of decision-making for automated driving. Therefore, the analysis of the information contents of the expert drivers' anticipatory driving in this study was focused on uncertainties they recognize and resolve related to the unfolding traffic events.

3 STUDY 1 – EXPERT SAMPLE VALIDATION: HAZARD PREDICTION TEST

3.1 Method

In Study 1, the expert sample validation with a hazard prediction test was done in order to verify that the selected driving instructors are able to anticipate unfolding hazardous traffic events by a better rate than inexperienced or a mixed group of non-instructor drivers. While driving instructors teach their students, they anticipate possibly hazardous events and therefore are more prepared to act if it seems that the student driver cannot manage the situation. Furthermore, driving instructors are experienced in verbalizing their anticipations during driving lessons. Thus, we argue that driving instructors are well-trained experts in anticipating unfolding safety-relevant driving situations. In addition, the intention was to validate that the selected experts are able to anticipate such events that may currently be highly challenging for automated driving technologies.

3.1.1 Stimuli

Eighty driving clips, provided by a commercial UK company that provides hazard perception tests for learner drivers, were reviewed to select clips for the experiment. For evaluating the clips, knowledge of the previously reviewed challenges of the current automated driving technologies and the analyses by Hubmann et al. (2018), Lake et al. (2017), Lv et al. (2018), Rasouli and Tsotsos (2019), and Schwarting et al. (2019) on differences between human cognition and automated driving algorithms were utilized. Based on the evaluation, each selected clip was required to contain an unfolding hazardous event that human drivers should be able to anticipate – if they spot the relevant visual cue(s) – and which automated driving technologies perhaps would not be able to detect or anticipate. This could cause the automated driving technology to brake suddenly or even cause an accident.

Eventually, after reaching mutual understanding by two researchers, 28 out of 80 (35 %) clips were chosen that met the set requirements (see Table 1). The original clips were filmed in the UK and therefore were mirrored to respond to right-hand traffic, more familiar to Finland where the research was conducted. To transform the hazard *perception* clips into hazard *prediction* clips, each clip was edited to end to a black screen just after the hazardous event started to unfold, following the method by Crundall (2016), Jackson, Chapman, and Crundall (2009) and Ventsislavova et al. (2019). Effectively, each selected clip contained a situation that would potentially develop into hazardous event if neglected, such as a truck blocking driver's view, a ball flying over a street, or a street being too narrow for two cars to travel side by side. Hazard prediction test was chosen over hazard perception test since it can better discriminate between experts and novices (Crundall, 2016; Jackson et al., 2009).

Uncertainty	**Situation(s) and environment(s) on parenthesis**	**Visual cue**	**Plausible difference in behavior – human driver vs. automated driving technology**	**# of clips**
Is the road too narrow to accommodate the driver's own car and oncoming cars?	Narrowing road (Street)	Narrowing road ahead with oncoming traffic	Human driver is able to anticipate that the road ahead is too narrow for all vehicles and therefore waits for the oncoming vehicle to pass or adjusts speed or lane position. Automated driving technology could continue driving without decelerating, causing sudden emergency braking or an accident. Possible problem: lack of scene understanding (Lake et al., 2017).	6
Is there occluded traffic crossing or merging?	Poor visibility (Street)	Stationary objects occluding moving vehicles	Human driver is able to notice the moving vehicle behind the stationary object and anticipate that the vehicle might turn towards and therefore decelerates gently. Automated driving technology may not be able the recognize the moving vehicle behind the occluding object, causing sudden emergency braking or even an accident. Possible problem: occlusion and lack of intuitive physics (Hubmann et al., 2018; Lake et al., 2017).	5
Is there oncoming traffic behind the vehicle that is to be passed?	Passing, curvy road, poor visibility (Highway, Street)	Passing required with poor visibility ahead (e.g., curvy road ahead, truck blocking part of the road)	Human driver can realize that due to poor visibility of the road ahead it is not possible to see if there is oncoming traffic approaching behind the vehicle that is to be passed. Human driver is able to anticipate that oncoming traffic is a possible scenario and therefore slows down. Automated driving technology could continue driving with the same speed resulting in sudden emergency braking or an accident in case of oncoming traffic. Possible problem: lack of scene understanding and intuitive physics (Hubmann et al., 2018; Lake et al., 2017).	4
Are the vehicles on parallel side road going to merge in front?	End of a parallel road, traffic merging (Street)	Vehicles driving on ending parallel side road	Human driver is able to anticipate that the adjacent side road is ending and vehicles on the road may join the main road ahead and therefore adjusts speed accordingly. Automated driving technology may not detect an ending side road and anticipate that the traffic will soon merge, causing a possible sudden emergency braking or even	3

Uncertainty	Situation(s) and environment(s) on parenthesis	Visual cue	Plausible difference in behavior – human driver vs. automated driving technology	# of clips
			an accident. Possible problem: lack of scene understanding and psychological reasoning (Lake et al., 2017).	
Is the faster vehicle in front going to change lanes?	Slower traffic ahead, faster vehicle on the adjacent lane (Freeway)	Vehicles having speed differences on a two-lane road (e.g., faster vehicle approaching slower vehicle on the adjacent lane)	Human driver is able to anticipate that the faster vehicle may pass slower traffic ahead and move into the driver's lane. Due to the prediction, human driver is able to be prepared and adjust speed more gently than automated driving technology and even avoid an accident. Possible problems: lane change in heavy traffic (Lv et al., 2018) and lack of psychological reasoning (Lake et al., 2017).	2
Is the road/lane too narrow to accommodate driver's own car and oncoming vehicles that are passing?	Slower traffic ahead, passing (Freeway, Street)	Oncoming vehicles or vehicles in front passing slower traffic (e.g., cyclists, motorcyclists) far ahead	Human driver is able to anticipate that the road is too narrow for all the vehicles to travel parallel and is, therefore, able to slow down and/or adjust the lateral position of the car. Automated driving technology may not be able to detect the trajectory deviation of the passing car and is therefore unable to adjust its own speed and lane position causing possibly a sudden emergency braking or an accident. Possible problem: lack of scene understanding (Lake et al., 2017).	2
Is there someone stepping out of the parked car?	Parked cars (Street)	Parked car's door opening / person inside a parked car	The sudden opening of parked car's door or seeing a person inside a parked car are cues to a human driver that the door may open entirely and blocking the driveway. Due to the anticipation, human driver is able to be prepared, yield, and decelerate more gently in advance than automated driving technology might. Possible problems: driving too close to a parked car (Lv et al., 2018) as well as lack of scene understanding and psychological reasoning (Lake et al., 2017).	2

Uncertainty	Situation(s) and environment(s) on parenthesis	Visual cue	Plausible difference in behavior – human driver vs. automated driving technology	# of clips
Is the pedestrian going to cross the street in front?	Pedestrian planning to cross the road (Street)	Pedestrians showing intentions to cross the road	Human driver is able to anticipate the trajectories of the pedestrians based on their behavior (e.g., looking both ways) or position even if they are stationary and, therefore, is cautious. Automated driving technology may not be able to recognize pedestrians' intentions since they are still on the walkway and not yet crossing. Sudden crossing could cause sudden emergency braking or an accident for automated driving technology. Possible problems: lack of understanding social cues (Rasouli and Tsotsos, 2019; Schwarting et al., 2019) and psychological reasoning (Lake et al., 2017).	2
Is the occluded pedestrian going to re-appear behind the object and cross the road in front?	Occluded pedestrian (Street)	Stationary object occluding walking pedestrian momentarily	Human driver is able to anticipate that the pedestrian may re-appear behind the van and cross the road and therefore decelerate accordingly. Automated driving technology may not able the recognize the existence of the pedestrian behind the van, causing sudden emergency braking or accident. Possible problem: momentary occlusion and lack of intuitive physics (Hubmann et al., 2018; Lake et al., 2017).	1
Is emergency vehicle approaching and yielding needed?	Emergency vehicle approaching (Street)	Emergency vehicle's blue lights are approaching	Human driver is able to notice well in advance the blue lights and anticipate that yielding maneuvers may have to be made. For automated driving technology, the emergency vehicle may be detected as a crossing object to be avoided like any other, but it may not have an understanding that yielding well in advance is compulsory. Possible problem: identifying emergency situations (Lv et al., 2018).	1
Are kids going to run onto the street after the ball?	Kids playing (Street)	Ball flying over the street	Human driver is able to anticipate that a ball flying over the street indicates playing kids ahead and decelerates in advance accordingly. The ball does not indicate playing kids to automated driving technology, which might lead to sudden emergency braking or even	1

Uncertainty	Situation(s) and environment(s) on parenthesis	Visual cue	Plausible difference in behavior – human driver vs. automated driving technology	# of clips
			an accident. Possible problem: lack of psychological reasoning (Lake et al., 2017).	
Is the cyclist going to yield?	Cyclist in a traffic circle (Street)	Cyclist slowing down and approaching a traffic circle	The cyclist in the traffic circle tries to maintain momentum and, as a result, does not stop but signals the driver of yielding by entering the traffic circle with a slower speed. Human driver can anticipate the yielding of the cyclist. Since the cyclist is not stopping before entering the traffic circle, automated driving technology could perform sudden braking. Possible problems: lack of understanding social cues (Rasouli and Tsotsos, 2019; Schwarting et al., 2019), lack of psychological reasoning and intuitive physics (Lake et al., 2017).	1

Table 1: Clips for hazard prediction test

3.1.2 Participants and experimental design

Participants were recruited via different mailing lists and by contacting driving schools directly. In total, 36 participants completed the experiment. The participants were divided into three groups: inexperienced (no driving experience, *n* = 12), mixed (varying driving experience, *n* = 12), and expert drivers (driving instructors, *n* = 12). The inexperienced group was included in order to test if hazard prediction ability comes with driving experience. A mixed group was included to represent large variation in cumulative driving experience, that is, to represent the driver population and to enable correlative analysis (experience vs. score). The driving instructor group was included to test if the formal training provides greater anticipation skills compared to a random sample from the driver population. Each participant had normal or corrected-to-normal vision. The demographics of the three participant groups can be seen in Table 2. It should be noted that the reported lifetime driving experiences in kilometers are estimations of the participants and they only include kilometers driven with cars. Since the kilometers are self-reported, the accuracy of estimations may vary between participants.

	Inexperienced group	Mixed group	Expert group
Age range	21–36	21–35	27–62
Mean age	*M* = 27.1, *SD* = 4.9	*M* = 27.1 *SD* = 4.8	*M* = 46.3, *SD* = 11.4
Gender	7 females, 4 males, 2 not disclosing gender	3 females, 9 males	3 females, 9 males
Range of driving experience in years	0	0.5 – 17	9.5 – 44
Mean driving experience in years	0	*M* = 8.4, SD = 5.2	*M* = 28.4, SD = 11.2
Range of self-estimated lifetime driving experience in kilometers	0 km	200 km – 1 000 000 km	280 000 km – 2 000 000 km
Mean self-estimated lifetime driving experience in kilometers	0 km	*M* = 202 475, *SD* = 331 317	*M* = 798 222, *SD* = 548 996

Table 2: Demographics of the participant in hazard prediction test

In order to study if the hazard prediction ability is a skill achieved with experience or if it can be rapidly learned with scenario-specific declarative knowledge (Rasmussen, 1983, 1982), half of the participants in each group (inexperienced, mixed, and experts) were primed with generic written examples of possible hazards presented in the video clips (e.g., the door of the parked car suddenly opens). None or weak effect of briefing would stress the importance of using experts as the source of information in the subsequent study. Thus, the experimental design was 2 x 3 (briefing x group).

3.1.3 Materials and apparatus

The duration of the hazard prediction test clips varied in length from 4 to 43 seconds. Dell laptop computer with an external 22” screen was used to display the hazard prediction clips to the participants. The clips were presented in a randomized order with SMI Experiment Center 3.0 (SensoMotoric Instruments GmbH). SMI RED 500 remote binocular eye-tracking system (sampling rate 500 Hz) was utilized to track participants’ eye movements (data not reported here). Sony HDR-XR500 video camera was used to record the participants’ answers. IBM SPSS Statistics 24 was used for data analysis. The experimental setup is illustrated in Figure 2.

Figure 2: The experimental setup

3.1.4 Procedure

Upon arrival, participants read and signed the informed consent form. After that, participants were seated 60 cm from the screen. Before the actual experiment, each participant practiced with watching four videos which ended with a black screen just after the hazardous event started to unfold, similar to the actual videos, and answering to following questions after each clip: 1) What was the risk factor?, 2) What was the location of the risk factor?, 3) What happens next?, and 4) How would you proceed in the situation? Participants were instructed to evaluate the unfolding situation at the end of the clip and give an answer to each question as they feel is the correct answer regarding the unfolding situation. The same questions were asked for the videos in the actual experiment with the same instructions. If the answers were insufficient, instructions were repeated. Each participant group (inexperienced, mixed, and experts) received the same general instructions.

After the practice, the participants belonging in the briefing subgroups were told that similar hazards were repeating in the videos presented, and before the experiment started, they were given out a written hazard list to familiarize themselves with. The participants belonging to the no briefing group were instructed to look for a risk factor at the end of the video, with no information about the risk types or their recurrence.

In the actual experiment, participants watched 28 hazard prediction video clips in randomized order, which ended with a black screen just after the hazardous event started to unfold. After each video, participants were asked to answer four questions as they previously practiced. A small break after every 10 videos was offered to each participant. During the experiment, participants' oral answers were recorded with a video camera. The experiment took approximately 1.5 hours, and after the experiment, each participant received a gift card (15 €).

After the experiment, participants' verbal reports were analyzed and rated by two researchers. They were given 0–3 points for one video in total, depending on whether the participant had explicitly recognized the risk factor and its location and anticipated the development of the situation correctly. Correct answers were also accepted if the participant recognized several risk factors, of which one was the correct answer for the video. The fourth question (How would you proceed?)

was not rated and the results are not reported here. Therefore, the maximum score for the videos was 84 points (3 x 28).

3.2 Results

Since the hazard prediction test scores and overall driving experience in kilometers were non-Gaussian, medians are reported here instead of means. The hazard prediction test scores (*N* = 36, interquartile range in parentheses) ranged from 12 to 48 points, and the overall median was 29 points (15). The median scores per group were: inexperienced 20.5 (11.0), mixed 30.0 (15.0), and experts 34.0 (10.0). The mean scores per group are illustrated in Figure 3.

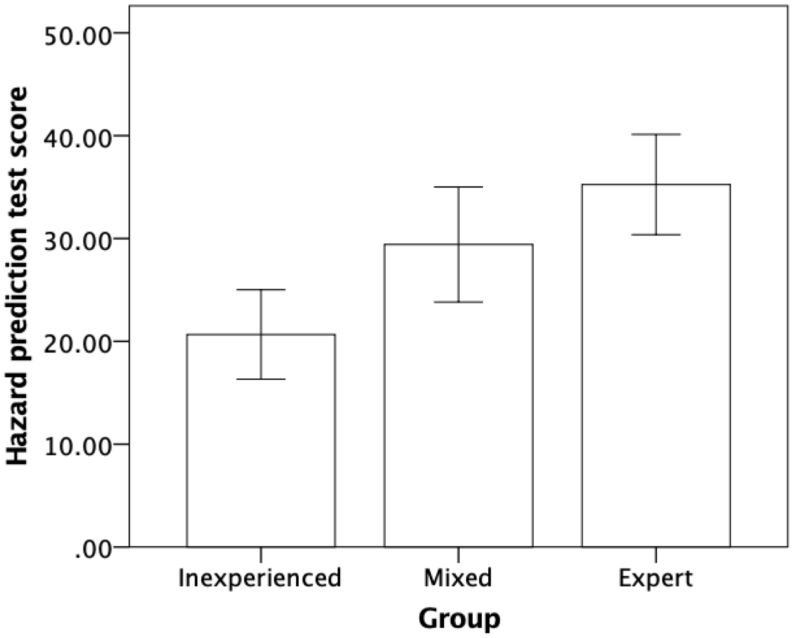

Figure 3: Hazard prediction test score per group (mean, *n* =12). Bars: 95% CI.

A factorial 2 x 3 ANOVA was conducted to investigate the interaction effects of briefing and group on hazard prediction test scores. There was no significant interaction between the factors (p = .490). Significant main effect of group was found on hazard prediction test scores: $F(2, 30) = 10.15$, p = <

.001, η_p^2 = .404 (large effect). Due to the non-gaussian hazard prediction test score distribution in the inexperienced group, pairwise comparisons between groups were conducted with nonparametric tests. Similar to ANOVA, Kruskall-Wallis H test indicated that there were significant differences in hazard prediction test scores between the different groups, $\chi^2(2) = 13.632$, $p = .001$. According to Mann-Whitney U test, there were significant differences between novices and mixed group, mixed group scoring higher ($U = 30.50$, $p = .016$, $d = 1.11$ [large effect size]) and between novices and experts, experts scoring higher ($U = 12.50$, $p = .001$, $d = 2.01$ [large effect size]). The effect size of the difference between mixed group and experts was moderate ($d = 0.71$), but the difference was not significant with this sample size ($U = 43.50$, $p = .099$, $n = 12$).

For testing the association between lifetime driving experience in kilometers and hazard prediction test scores, Spearman's rank-order correlation was used. For the analysis, the group of novices was omitted since they do not have any driving experience, and therefore here $N = 24$. A moderate association between driving experience and hazard prediction test scores was found (see Figure 4): $\rho = .425$, $p = .038$. However, even though the association between age and driving experience was strong ($\rho = .834$, $p < .001$), there was no significant association between age and hazard prediction scores ($\rho = .241$, $p = .256$).

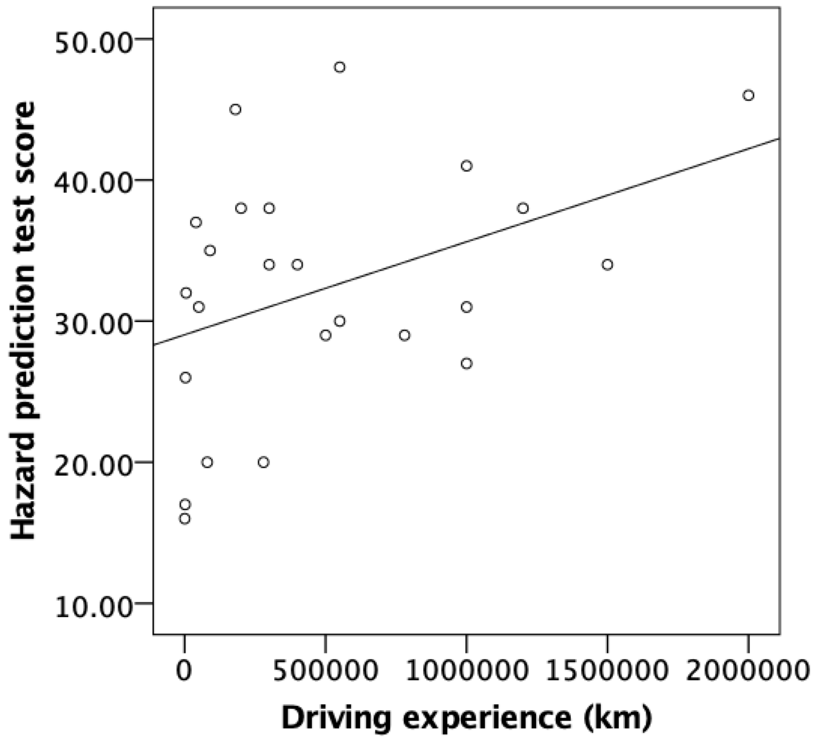

Figure 4: Hazard prediction test score per lifetime driving experience (*N* = 24).

3.3 Discussion

Based on the results, the driving instructors can be considered as experts compared to the inexperienced and also at least a subsample of them compared to the mixed group of non-instructor drivers. A moderate association between driving experience and hazard prediction test scores was found, which suggests driving experience can explain some of the variance in the scores. This is consistent with previous studies (e.g., Crundall, 2016; Jackson et al., 2009; Stahl et al., 2016; Ventsislavova & Crundall, 2018) and implies that the ability to anticipate traffic situations evolves with experience. It should be noted that the lifetime driving experience in kilometers was self-estimated and there could be differences between individuals how accurately they can estimate their experience. However, the correlation between age and experience and insignificant correlation between age and test score suggest general validity of the self-reported driving experience measurement, even if there might be inaccuracies in individual reports.

However, the driving experience does not alone explain the drivers' hazard prediction test scores. Further, since novices were also able to score in hazard prediction test above chance, anticipating hazardous situations is something that humans may be able to do at some level regardless of driving experience – perhaps with the help of intuitive psychology and intuitive physics, causal reasoning, and utilizing previous experiences in other domains (Lake et al., 2017). However, priming of participants with declarative knowledge about possible hazardous scenarios did not affect the scores. This may be due to a number of factors but suggests that the anticipation skills cannot be acquired based on written examples, at least in the short time provided to study the model scenarios. This finding stresses the importance of using domain experts as the source of situational information in studies such as our following on-road study.

4 STUDY 2 – FIELD STUDY WITH EXPERTS: ANTICIPATION IN REAL TRAFFIC WITH PROSPECTIVE THINKING-ALOUD

4.1 Method

In Study 2, six experts – validated with the hazard prediction test – took part in the field study where they were prospectively thinking aloud of unfolding traffic situations while driving on public roads. The purpose of the field study was to examine what driving-task relevant the experts are anticipating to happen.

4.1.1 Participants

The ages of the participants ranged from 36 to 56 (*M* = 47.5, *SD* = 10.5), lifetime driving experience from 280 000 to 2 000 000 kilometers (*M* = 696 667, *Mdn* = 525 000, *SD* = 649 821) and teaching experience from 5 to 38 years (M = 10.8, Mdn = 9.0, SD = 14.1). Their mean score in the hazard prediction test was 34.5 points (SD = 10.7). Three of them belonged to the no-briefing group and three of them to the briefing group in the validation experiment.

The ethical review board was inquired about the requirement of ethical approval and the study was allowed to take place after installation of a secondary brake pedal for the experimenter for the case of emergencies.

4.1.2 Materials and apparatus

The length of the predefined route was 57.2 kilometers (see Figure 5) and driving the route took approximately one hour and ten minutes. The route was selected to contain a representative sample of local road environments: freeways (with controlled access), two-way highways, as well as suburban and city streets, and a parking lot.

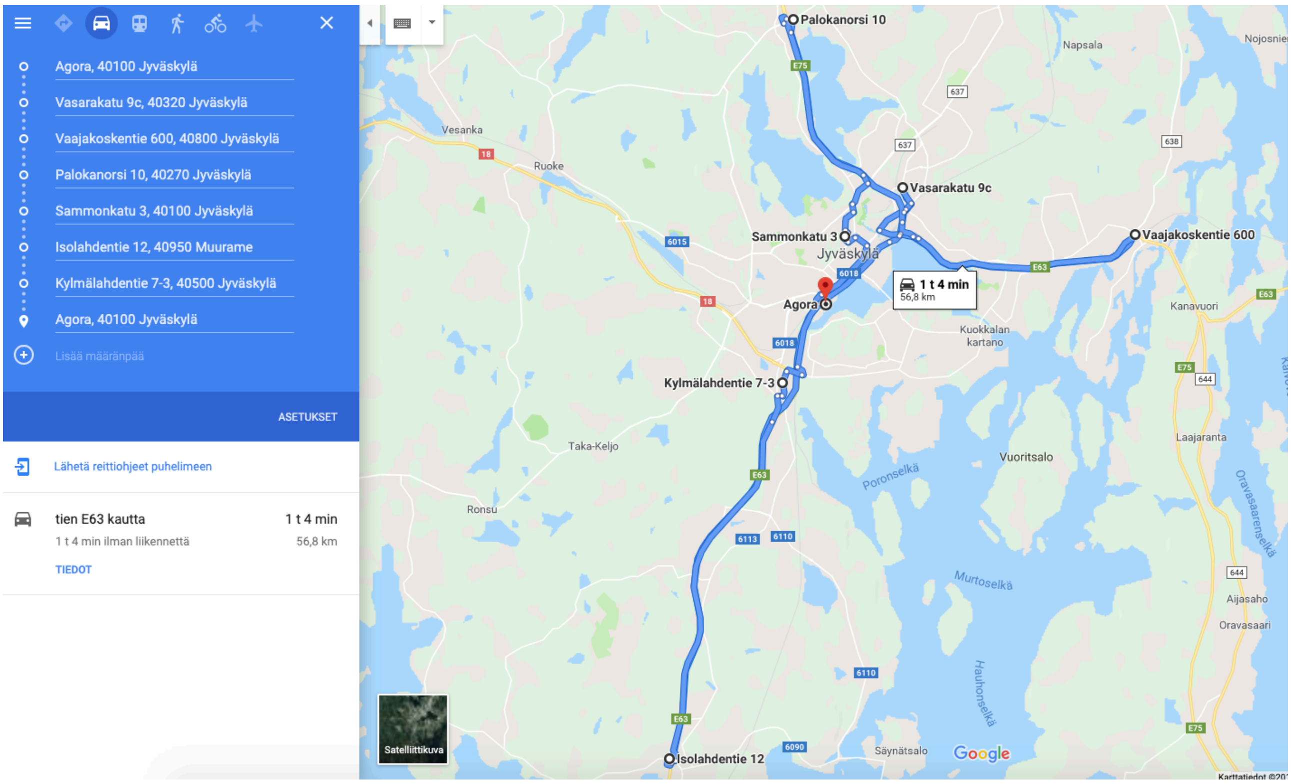

Figure 5: The predefined route used in the study.

Toyota Prius (2009) with an extra brake pedal was used in the experiment. For recording the road scene and thinking-aloud data, MoviePro application for iPhone 8 and an external microphone was used. Google Maps application, running on 10.5” iPad Pro, was used for providing route guidance (see Figure 6). Speedometer application was placed next to the route guidance for enabling recording the GPS speed on the video. Participants’ eye movements were recorded with head-mounted Ergoneers’ Dikablis Professional eye-tracking system (data not reported here). Transcription of the thinking-aloud data was done using Noldus Observer XT 12 software.

Figure 6: Backseat view from a video.

4.1.3 Procedure

After informed consent and before the experiment started, each participant watched two training videos (1.40 minutes and 0.28 minutes) that were recorded on the same roads they were about to drive. While they watched the videos, they were instructed to anticipate aloud what driving-task relevant is going to happen next in the traffic and how it affects their behavior and maneuvering. As for the feedback during the training videos, we encouraged the participants to verbalize more actively the unfolding traffic situations, if necessary, which is typical for the thinking-aloud method.

After they were familiar with the prospective thinking-aloud method, they received the instructions for the drive. They were asked to obey traffic rules and follow the predefined route. During the drive they would be prospectively thinking aloud as they had practiced earlier. Theoretical models of multitasking performance, such as Wickens' (2008) Multiple Resources Theory, suggest that concurrent verbal-vocal tasks during visual-manual tasks (e.g., driving) do not interfere severely with each other. Further, according to Drews et al. (2008), when the topic of the conversation while driving is the surrounding traffic, it helps the driver to share situation awareness with the passenger. In our study, the experts were talking about the prevailing traffic and driving situations, and therefore we suggest that the think-aloud protocol did not distract them. In addition, the driving instructors are used to verbalizing driving situations to their students.

Further, Drews at el. (2008) propose that if the driving condition is demanding, the complexity of the conversation decreases. Before the on-road study, we gave instructions to our experts that if the driving situation needs their full attention, they can communicate it after the situation is under control. There were occasions where the drivers used this opportunity and the confronted uncertainty was communicated after the situation had cleared.

All participants completed the same route approximately at the same time in the afternoon close to rush hours in order to have more potential interactions with other traffic (with one exception:

noon). The visibility during the trials was normal, although there was a light rain shower during the drives of two participants. After completing the route, the expert drivers received a gift card (15 €).

4.1.4 Data analysis

The prospective thinking-aloud data consists of six audio-visual recordings in real traffic. On average, one recording lasted for 1 hour and 10 minutes (time range from 65 to 75 minutes). The prospective thinking-aloud data from the videos were transcribed into textual format, resulting in 1277 utterances. The utterances were transcribed according to the start and the end of a comment. In addition, driving speed when the comment started and the speed when the comment ended were coded based on the GPS speed visible in the videos. On average, one participant produced 212 utterances (range: 80–408). In total, 124 utterances were excluded from the analysis, as their contents were not notions of uncertainty, such as “The pavement has been repaired a bit” and “That is good”. Thus, individual notions of uncertainty were analyzed from a total of 1152 utterances. It should be noted that one utterance could include more than one uncertainty notion. Through this analysis, 1881 individual notions of uncertainty were listed. On average, one participant produced 313 individual notions of uncertainty (range: 150–684).

A conceptual framework was developed to aid qualitative content analysis of the prospective thinking-aloud data. The framework provides a theoretical lens to guide the analysis, but not in a restricting or excluding manner. Thus, contents outside of the conceptual framework are analyzed with inductive content analysis (Mayring, 2000), if relevant to the research problem. A conceptual framework explicates the focus of the analysis by constructs, key factors or variables, and possibly the presumed relations among them (Miles and Huberman, 1994). Here, the focus was on examining driving-relevant uncertainties. Therefore, the conceptual framework consists of the following factors: uncertainty, environment, and goal.

The first factor, uncertainty, is defined as the unpredictability of a task-relevant event state (Clark, 2013) and is a central factor in the conceptual framework guiding the analysis. Contents of uncertainties were analyzed from the data with inductive content analysis (Mayring, 2000). The second factor, environment, consists of components that are defined according to the selected driving route. These components are freeway (with controlled access), highway (with two opposite lanes and crossings), street, traffic circle, and parking lot. The third factor of the framework, goal, consists of safety, economy, comfort, and wayfinding. Safety, economy, and comfort were selected based on the reviewed literature representing higher-level goals in driving and indicating these three as the main goals of improvement in automated driving technology. Wayfinding is an additional goal that is typical at the strategic level of driving (Matthews et al., 2001).

The conceptual framework also assumes relationships between the factors (Miles and Huberman, 1994). Here, the factors are related to each other in a context-dependent manner. The focus of the analysis was to understand what kind of uncertainties are expressed in what kind of contexts and to what kind of goals these uncertainties relate to.

Qualitative content analysis was conducted with the aid of the conceptual framework. Qualitative content analysis is utilized in systematic text analysis. The goal is to categorize information contents, usually with an inductive approach (Mayring, 2000). A central benefit in conducting inductive content analysis is its ability in detecting and developing categories with rich descriptions through analysis iterations of the information contents under analysis. In the iterative development process of the descriptive categories, overlapping categories were re-analyzed to be merged (Mayring, 2000). The analysis of the prospective thinking-aloud data for enabling cognitive mimetic design of automated driving solutions followed this procedure.

First, the environments were coded from the transcriptions and from the video recordings to ensure correct coding. All the videos were transcribed by two independent transcribers in sequential order, to diminish the possibility of rater factor to occur (see e.g., Gwet, 2014). Second, by further familiarization of the data, a category of situations was inductively developed as one independent entity. Situations were defined based on the transcribed sentences together with the synchronized videos as temporary issues and conditions occurring in specific environments. The descriptive subcategories of situations (e.g., traffic lights, road construction, traffic sign, exit ramp, intersection, congestion) were created through inductive content analysis. After this, two coders, who were present during the original drives, analyzed the data. Coder 1 sorted all the data in Excel according to environment and situations in order to begin the context-dependent extraction of expressed uncertainties. If the uncertainty notions were difficult to understand due to the context-dependent sorting, the original sorting of the data by timestamp was displayed to ensure correct categorization of the uncertainty notions by the sentences preceding or following the sentence in question. The final uncertainty category consists of 83 descriptive subcategories that were written in the form of a question in order to illustrate the uncertainty related to the specific situation (cf. Table 1).

The category titled as action was developed to illustrate context-dependent uncertainty-related adaptive actions. The category of actions was analyzed by Coder 1 from the sentences if action-related notions were made. All notions did not include actions to be carried out. Uncertainty categories were iterated to develop a final set of subcategories to represent different uncertainty notions. After this, the data was further synthesized by analyzing goal (safety, economy, comfort, wayfinding) for each of the uncertainty subcategory. After Coder 1 had extracted the uncertainty notions and categorized these into subcategories, Coder 2 went through these coded uncertainties and possible divergent interpretations were discussed and resolved. After this, the number of notions and participants per notion for each uncertainty subcategory was calculated as presented in Tables 3 and 4. Finally, Coder 2 translated all the categories and selected example quotations into English and Coder 1 went through the translations to inspect that that there were no details lost during the translation process. Due to the nature of the process, we were not able evaluate inter-rater reliability numerically but these was a high level of agreement among the two coders in each step.

4.2 Results

The most important of the final uncertainty subcategories (83) that were related to safe, economical, and/or comfortable driving are listed in Tables 3 and 4. However, there were some subcategories that were excluded from the results. Six subcategories related to wayfinding (e.g., Are we on the route?; To which direction should we continue now?) were found – these are omitted from the results, as navigation should not be a challenge to current automated driving technologies. Some of the uncertainties are highly relevant for a human driver (e.g., What is the current speed of the car?; Is someone approaching in the blind spot?) but irrelevant for automated driving technology and were left out from the data. The rest of the excluded subcategories are relevant also for automated driving technologies but should be easily resolved by the current level of technology (e.g., Are there oncoming cars or pedestrians ahead?; What is the speed limit?; Are there cars beside or behind our car?; Is it slippery?). All of these mentioned uncertainties (20) were excluded from this report. These excluded uncertainties include the only uncertainty notion that was related to the operational level of control of the vehicle (i.e., Can I hold the control of the car?) – all the other uncertainties were related to tactical or strategic level situation awareness (Matthews et al., 2001).

First, Table 3 presents uncertainties (34, 54%) of other road users' behaviors, awareness and/or intentions. Then, Table 4 lists all the uncertainties (29, 46%) that are not (directly) related to behaviors, awareness or intentions of other road users. Both tables also include those uncertainties that were related only to a few notions, as these may be important even if the traffic conditions did not lead to these kinds of situations for all the participants. The Goal category can relate to one's own as well as other road users' safety, comfort and/or economy.

Uncertainty	Situation(s)	Environment(s)	Goal	Expert’s example quotation indicating uncertainty	Action(s)	Notions (n)
Are other road users aware of my intentions?	Turn, lane change, exit ramp, merge, traffic circle exit, parking	Street, traffic circle, freeway, highway, parking lot	Safety, comfort	“Slowly we drop our speed and now turn signal on to indicate that we are turning – let’s tell that to others too. Well, well, there is a friendly co-driver, and this is how it goes.”	Use of turn signal in advance, alignment, soft deceleration, creeping, way giving, turn signal off, eye contact	101 (6)
Is there going to be a rear-end collision?	Traffic lights, intersection, exit ramp, driving in traffic queue, bus travelling behind, animal transport travelling behind	Freeway, street, traffic circle, highway	Safety	“That red car behind us is quite close. But no worries, we are keeping good following distance and we are not going to do anything sudden.”	Distance, decelerating slowly, checking rear-view mirror, avoiding sudden braking, anticipatory deceleration, alignment, use of turn signal in advance	78 (6)
Who is obligated to yield?	Traffic lights, 4-way intersection, intersection with yield sign, crosswalk, turning, stationary bus, entrance ramp	Street, traffic circle	Safety	“Arrow light, there shouldn’t be anyone we should yield. Then equal crossroads – cars approaching from the right-hand side and from ahead, but those are so far that they will not disturb us.”		69 (6)
Are others obeying traffic rules?	Traffic lights, driving order in intersections, obligation to yield, turn, crosswalk, entrance ramp, speed limit, pedestrians not using crosswalk for crossing, drivers don't know how to drive in a two-lane traffic circle	Street, traffic circle, freeway, highway	Safety	“We have a green arrow light, therefore there shouldn’t be any pedestrians ahead but still there is a chance that someone comes behind the yield sign.”	Deceleration, way giving, eye contact, yielding, being adaptable, checking rear-view mirror, distance, creeping, pulling away slowly in traffic lights	63 (6)

Uncertainty	Situation(s)	Environment(s)	Goal	Expert's example quotation indicating uncertainty	Action(s)	Notions (n)
Is the vehicle's following distance sufficient (behind us)?	Driving in traffic queue	Freeway	Safety	"The car behind us is not keeping safe following distance to us and that's why we need to keep extra distance to the car in front of us."	Checking rear-view mirror, avoiding sudden movements, keeping steady speed	25 (6)
Do other drivers need a lane change?	Lane change, entrance ramp	Street, freeway	Safety, comfort	"Then we are reducing the speed and keep distance to the car in front of us if someone on the parallel lane wants to change lanes."	Deceleration, distance, way giving	15 (5)
How is the traffic far ahead on the route?	Exit ramp, end of freeway, curve, congestion, entrance ramp	Traffic circle, freeway, highway, street	Safety, economy	"At this time, there must be a traffic congestion."	Deceleration	13 (6)
Is parked car's door going to open?	Road construction, rain, parked cars, narrow streets	Street, parking lot	Safety	"We shouldn't drive (too close to the parked cars) in a way that our side mirrors bang – there is a chance that the parked car's door will open suddenly."	Distance between own and parked cars	11 (4)
Is other traffic keeping safe following distances?	Driving in traffic queue	Highway, freeway	Safety	"I can see brake lights. That black car is too close to that other car."	Distance, steady speed	10 (5)
What are the intentions of other road users?	Turn, lane change, merge, intersection, pedestrian	Street, highway	Safety, comfort	"Interesting to see what that white car is planning to do."	Deceleration	10 (4)
Do other drivers need a last minute's lane change?	End of lane, end of freeway	Highway, freeway	Safety, comfort	"The parallel lane is ending so we should observe the left-hand side mirror in case there is still someone rushing to our lane."	Checking rear-view mirror	9 (3)

Uncertainty	Situation(s)	Environment(s)	Goal	Expert's example quotation indicating uncertainty	Action(s)	Notions (n)
Are other vehicles able to enter the freeway?	Entrance ramp	Freeway	Safety, comfort, economy	"The main thing is not to brake suddenly in these kind of situations [others entering the freeway] but releasing throttling usually helps co-drivers to accelerate enough."	Way giving, slowing down, checking mirrors, distance	9 (3)
Is there an emergency vehicle approaching?	Chance of emergency vehicles	Street, parking lot, highway	Safety	"There's green arrow light but still it's good to check that there are no emergency vehicles approaching."	Checking rear-view mirror	9 (3)
How is the traffic queue moving?	Driving in traffic queue, traffic lights, intersection, heavy traffic	Street, highway	Safety, comfort, economy	"Traffic lights change to green but there's a big truck in front, so the queue is not moving fast. That means that there's no rush to move forward and I'll show that to my co-drivers too.	Looking far ahead, checking rear-view mirror, use of turn signal, driving in neutral gear	8 (3)
Is there a train approaching?	Crossing train tracks	Street, railroad crossing	Safety	"Everyone should remember to pay attention when crossing train tracks. You never know what happens there."	Deceleration	7 (6)
Is oncoming traffic passing (two lanes)?	Passing	Highway	Safety, comfort	"This road is changing into two-lane road. It means that now we have to observe oncoming traffic and their possible passing."	Deceleration, way giving	6 (4)
Is someone in front going to change lanes?	End of lane, intersection, traffic lights	Street	Safety, comfort	"Then the parallel lane is ending but no one is there."	Deceleration, distance	6 (3)

Uncertainty	Situation(s)	Environment(s)	Goal	Expert's example quotation indicating uncertainty	Action(s)	Notions (n)
Is the traffic queue moving?	Traffic lights	Street	Comfort	"Let's make sure that the queue is moving nicely and no one's engine shuts off or something like that."	Driving in neutral gear, slow speed	6 (2)
Why is the traffic queue slowing down/ stopping/congested?	Driving in traffic queue, intersection, oncoming traffic	Street, highway	Safety, comfort	"I bet there is a big truck ahead making a wide turn."	Deceleration	5 (3)
Are there children on sidewalk/behind parked cars?	Turning, children crossing sign, daycare nearby, parked cars	Street	Safety	"Well, are there small pedestrians behind the car?"		5 (3)
Can others see my vehicle?	Rain, distracted drivers, pedestrian crossing street	Highway, parking lot, street	Safety	"I'll check that the headlights are on because I'm not sure if they work automatically. Due to rain, I want to make sure that I'm visible to others."	Head lights, eye contact	4 (4)
Are we approaching an intersection at the same time (merging)?	Merging, curve, end of lane	Freeway	Safety, comfort	"There's a curve ahead, we are not yet going to accelerate and we need to keep safe following distance so we all aren't in the intersection at the same time – you never know what kind of drivers there are going to be."	Distance, monitoring other traffic	4 (3)
Is other road users' visibility sufficient?	Large vehicles	Freeway, highway	Safety, comfort	"There is a car approaching on the entrance ramp. Since it's a van, it can't necessarily see us."	Distance, deceleration	4 (2)

Uncertainty	Situation(s)	Environment(s)	Goal	Expert's example quotation indicating uncertainty	Action(s)	Notions (n)
Is the car in front rolling to my car's nose?	Traffic lights	Street, highway	Safety	"If we drive close to the car that is in front of us, there's always the risk that it will roll to our nose."	Distance	3 (3)
Is the passing vehicle able to pass?	Passing	Freeway	Safety, comfort	"There's a car passing us, let's release the throttle a bit and it will be able to pass us smoothly."	Deceleration, checking mirrors	3 (2)
Is someone cutting in?	Exit ramp	Freeway	Safety, comfort	"Now someone started passing behind us. But it doesn't bother us because I don't think that it will cut in."		3 (2)
Is the bus merging in front of my car?	Bus merging from bus stop	Highway	Safety	"Okay, that bus is merging from the bus stop, well, and there it is – in front of us."		2 (2)
Is the truck with a trailer able to change lanes?	Lane change of truck with trailer, short entrance ramp	Freeway	Safety, comfort	"There is a green truck with a trailer in the intersection. Let's see when it will join the traffic."		2 (2)
Are there vehicles turning behind the bus?	Intersection, turning	Street	Safety	"Well, it seems that no one is approaching behind the bus, I can turn now."		2 (1)
Is someone approaching behind parked cars?	Parked cars, on-street parking	Street	Safety	"There are parked cars on the right-hand side, let's pay attention if someone is coming behind them."		1 (1)

Uncertainty	Situation(s)	Environment(s)	Goal	Expert's example quotation indicating uncertainty	Action(s)	Notions (n)
Is a truck going to cause rear-end collision behind?	Line and truck behind keeping short following distances	Freeway	Safety	"I'm checking the queue behind, there's a truck really close to other cars. Now it's really important that we don't brake suddenly because the queue behind is so tight – so to speak."	Avoiding sudden braking	1 (1)
Is someone passing in front of my car in the same lane?	Driving in traffic queue	Highway	Safety, comfort	"If someone in front starts passing, we have to act along if it looks that the passing car is unable to return to its own lane in time – we will not start to compete, we rather slow down and help."	Deceleration, way giving	1 (1)
Are other vehicles able to change lanes safely?	Entrance ramp	Freeway	Safety, comfort	"Here we have to pay attention to traffic merging from right – sometimes you see quite interesting lane changes there."		1 (1)
Will driver behind notice if her/his car starts to nose?	Traffic lights, driver behind is reaching something from the floor	Street	Safety	"The driver behind us has lost something and is trying to find it from the floor. Hope he has hand brake on and won't nose and cause a head-on collision."		1 (1)

Table 3: Uncertainties of other road users' behaviors, awareness and/or intentions (sorted by number of notions, *n*)

Uncertainty	Situation(s)	Environment(s)	Goal	Expert's example quotation indicating uncertainty	Action(s)	Notions (*n*)
What is the proper approach speed?	Curve, exit ramp, entrance ramp, traffic lights, speed limit signs, keeping safe following distance, turning, acceleration, traffic queue ahead, speed limit change ahead	Street, traffic circle, freeway, highway, parking lot	Safety, comfort, economy	"Traffic circle ahead, I'll let the speed drop slowly, 20 km per hour is an optimal speed in this traffic circle."	Deceleration, driving in neutral gear, Accelerating, increasing following distance, forcing others to decelerate near crosswalks, way giving, checking rear-view mirror, avoiding sudden braking	120 (6)
Is the following distance sufficient?	Traffic lights, speed limit, congestion, rain, passing, entrance ramp, entrance ramp (others), road construction	Street, freeway, highway	Safety	"I will release the throttle a little bit – in case that car will merge in front of us. That way we will keep safe following distance."	Distance, checking mirrors, deceleration, way giving	69 (6)
What is a safe gap to merge?	Intersection, entrance ramp, traffic circle entrance	Street, traffic circle, freeway	Safety	"And then there is a good gap for us to merge, yes that yellow car is so far away that it is save to merge."	Use of turn signal, deceleration, driving in neutral gear, alignment, way giving, speed adjusting, checking blind spot	67 (6)
Is stopping in the traffic lights needed?	Traffic lights	Street, highway	Safety, comfort, economy	"And the journey continues, those traffic lights seem to be red so there's no rush to get there just to wait in traffic lights."	Driving in neutral gear, deceleration, checking traffic lights of crossing traffic, checking rear-view mirror	61 (6)
When is changing lanes safe?	Lane change, traffic lights, entrance ramp	Street, traffic circle, highway, freeway	Safety	"There comes a van, I have turn signal on – then it's our turn to merge."	Way giving, use of turn signal, checking mirrors, checking rear-view mirror, checking blind spot, deceleration, accelerating, strong accelerating	47 (6)

Uncertainty	Situation(s)	Environment(s)	Goal	Expert's example quotation indicating uncertainty	Action(s)	Notions (*n*)
Is the visibility sufficient?	Turning, intersection, crosswalk, exit ramp, other cars in entrance ramp, weather, traffic in front, rain	Street, traffic circle, freeway, highway, parking lot	Safety	"In this situation, let's devote to keeping sufficient following distance. There is a big truck in front of us, we don't want to drive too close to the truck since it makes it hard to see what is happening in front of it."	Distance, deceleration, creeping, distance, driving slowly	45 (6)
Is stopping needed?	Turning (car in front), braking (car in front), congestion, congestion in traffic circle	Street, traffic circle, highway, freeway	Safety, comfort, economy	"That car in front of us is going to turn. So, let's release the throttle."	Distance, deceleration, driving in neutral gear	35 (6)
Is the road/lane too narrow?	Narrow street, parked cars, turning on highway, alignment	Street, highway, parking lot	Safety	"Again, the street is narrow and there is an oncoming car. Let's wait here until the car passes us and then we have more space to turn."	Deceleration, alignment, way giving, checking mirrors	25 (6)
Are the road constructions causing exceptions in traffic arrangements?	Construction work sign	Street, freeway	Safety	"Construction work zone. There are no contemporary speed limit signs but still it's reasonable to be cautious if there are construction workers present."	Alignment to the right, way giving, deceleration, driving in neutral gear, changing lanes, use of turn signal in advance	23 (6)
Is braking needed?	Slower traffic ahead, exit ramp, road construction, moose warning	Highway, freeway	Safety, comfort, economy	"We are catching up the car in front of us. Let's release throttle and see to what speed that car is adjusting to."	Checking shoulders, deceleration, checking rear-view mirror, passing, engine braking	17 (5)
When can I start moving again?	Traffic lights, intersection, queue	Street, highway	Comfort, economy	"And slowly the queue starts to move forward."	Checking traffic lights of crossing traffic, 'sliding'	14 (4)

Uncertainty	Situation(s)	Environment(s)	Goal	Expert’s example quotation indicating uncertainty	Action(s)	Notions (*n*)
When are the traffic lights going to change?	Traffic lights, intersection, driving order	Street, highway	Comfort	“The traffic lights on left changed to yellow. That indicates that ours are going to change to green soon. And that’s exactly what happened.”	Deceleration, checking traffic lights of crossing traffic, ‘sliding’	13 (4)
Is there time to cross the intersection before the traffic lights change into red?	Traffic lights	Street	Safety, comfort	“I will pay attention to traffic lights and check if we have time to turn before the light turns into red, I’m not just following the traffic.”	Creeping, way giving	13 (4)
Are the traffic lights going to change?	Approaching traffic lights	Street, highway	Safety, comfort	“Is the light going to change to red? No.”	Deceleration	11 (5)
Is braking needed in curve?	Exit ramp, entrance ramp	Street, freeway	Safety, comfort, economy	“The curve is quite sharp before the acceleration lane and that’s why we shouldn’t drive too fast.”	Deceleration, driving in neutral gear	11 (4)
What is the proper pace to slow down?	Driving in traffic queue, speed limit sign, traffic lights	Street, freeway, highway	Comfort, economy	“Slowly we brake and that way we don’t scare drivers in front of us or behind us.”	Deceleration, driving in neutral gear, checking rear-view mirror, deceleration efficiently but safely	9 (2)
Is passing needed?	Slower traffic ahead, 100 km/h speed limit	Freeway	Safety, comfort, economy	“There’s going to be 80 km per hour speed limit soon so it’s not reasonable to pass that guy – when our cars are side by side, the 80 km per hour zone starts.”	Deceleration	8 (4)

Uncertainty	Situation(s)	Environment(s)	Goal	Expert's example quotation indicating uncertainty	Action(s)	Notions (*n*)
Do I hit a pothole/object on the road?	Pothole on pavement, (small) object on the road, roadkill	Street, highway	Comfort	"Let's avoid those potholes on the pavement – that way it's more comfortable to drive."	Yielding, continue driving without yielding	7 (4)
When is the proper time to slow down?	Entering exit ramp	Freeway, highway	Safety, comfort, economy	"The car behind is really close to us. That's why I'm not going to brake strongly, more like throttling back so there is no surprise to the driver behind."	Use of turn signal in advance, checking rear-view mirror, deceleration at the exit ramp	7 (2)
If needed, is there space to yield to the adjacent lane?	Traffic merging, entrance ramp	Freeway	Safety, comfort	"There's an entrance ramp so it's good to check the left-side mirror and make sure that there is not a tight situation forcing us to yield – that's the last straw."	Checking left mirror, staying on own lane, way giving	5 (3)
Do I block the sidewalk?	Intersection, crosswalk	Street	Safety, comfort	"There is still enough space behind the car for pedestrians to cross."	Distance, alignment	4 (3)
Do I cause a rear-end collision?	Car in front, traffic lights	Street	Safety, comfort	"There's turning car in front, let's give proper time for the driver to turn."	Distance	4 (1)
Is sudden braking needed?	Driving in traffic queue	Traffic circle, highway	Safety, comfort, economy	"We have time to steadily slow down before the traffic circle and then we observe if sudden braking is needed."	Deceleration, use of turn signal, distance	3 (2)
Where can I park (safely)?	Parking	Parking lot	Safety	"In here the risks are these other cars starting off – at least there, that one on the left. And then we reverse."	Deceleration	2 (1)

Uncertainty	Situation(s)	Environment(s)	Goal	Expert's example quotation indicating uncertainty	Action(s)	Notions (*n*)
Are there equal intersections ahead?	Speed limit sign, intersection	Street	Safety	"40 km per hour zone starts here, which indicates that there could be equal intersections ahead."		2 (1)
Is there enough space to pass?	Traffic lights	Highway	Safety, comfort	"There should be proper distance between us and the car in front of us – if that car breaks down, we can still pass by going around the car and we don't have to reverse."	Distance, deceleration	2 (1)
What is the safest driving line?	Traffic queue	Freeway, highway	Safety	"And certainly, we should drive [on the lane] as right as possible, and actually – there is a mention in the law that one should drive as right as possible."	Alignment	2 (1)
Is the entrance ramp long enough for merging?	Merging	Freeway	Safety, comfort	"No one is coming, then the entrance ramp – which is short – and then we speed up strongly and check again that no one is coming."	Accelerating with force	1 (1)
Is it possible to drive uphill at a steady speed?	Hilly road	Highway	Comfort, economy	"Now we start to accelerate because there is an uphill and we don't want our speed to drop."	Accelerating in advance before uphill	1 (1)

Table 4: Uncertainties not (directly) related to the behaviors, awareness, or intentions of other road users (sorted by the number of notions, *n)*

4.3 Discussion

Most of the expressed uncertainties related directly to the behaviors, awareness, or intentions of other road users (54%, Table 3). These uncertainties include, for instance, recognizing other road users' intentions, signaling own intentions to them, other road users' lane changing actions, and other's situation awareness (e.g., Is other traffic keeping safe following distance?; Is other road users' visibility sufficient?). A notable uncertainty in Table 3 is related to the possibility – or even expectation – that others will not obey traffic rules. Central actions related to resolving these uncertainties are deceleration (slowly), giving way to others, increasing following distance, giving turn signals well ahead, and eye contact. Some of the uncertainties related to social behavior in traffic that have also been raised in previous studies (e.g., Brown & Laurier, 2017; Chater et al., 2018; Mahadevan et al., 2018; Rasouli & Tsotsos, 2019; Vinkhuyzen & Cefkin, 2016).

However, there were also a number of other types of uncertainties that are not, at least directly, related to the behaviors of other road users (46%, Table 4). Many of these uncertainties relate to one's own behavior, for example, what is the proper speed and safe deceleration/acceleration rate, is the headway distance sufficient, when there is a sufficient gap to merge or change lanes, and is the alignment of the car on the lane such that there is sufficient space for other road users (if needed). Some relate to one's own situation awareness, such as visibility ahead, and interactions with traffic lights and other cars standing in these. Central actions to resolve these uncertainties were similar to those in Table 3, for instance, keeping distance, driving with a steady speed, decelerating slowly, accelerating slowly or with force when required, and alignment.

Whereas one could argue that many of the uncertainties in Table 4 are due, in the end, also to the necessity to interact with other road users, these are more related to uncertainties of what are the optimal ways to control one's own vehicle in the arising situation to increase safety, fluency, comfort, and economy in the traffic system, instead of uncertainties related directly to social behaviors. It is worthwhile to stress that the uncertainties expressed by the human expert drivers did not only focus on ensuring one's own, but also other road users' safety, comfort, and economy. Most of the listed goals were related to safety. There are only six uncertainties that are not directly related to safety, and only one of these is under the uncertainties related to social behaviors in Table 3.

The method of the field study was similar to the methodology used by Kircher and Ahlström (2018). However, the emphasis was here on the prospective thinking-aloud and the focus of analysis on the anticipations and uncertainties of the expert drivers, as justified in related literature, whereas Kircher and Ahlström (2018) focused on evaluating the utility of various methods to assess driver's attentional state. They found and stressed the importance of taking into account the intentions of the driver for this analysis, and that thinking-aloud was an appropriate tool to gain insight into the driver's actual situational mental representations. Kircher and Ahlström (2017; 2018) argue that there is currently not enough a priori understanding of the minimum attentional requirements for safe driving applicable to any given driving situation. They suggest that prototypical situations and maneuvers in traffic as well as the situationally relevant information targets and agents in these should be defined to accumulate this understanding. The prospective thinking-aloud method seems to serve also for this purpose, and in particular, of studying the minimum information requirements related to the sufficient Level 3 situation awareness in real-world scenarios (Endsley, 1995).

Most of the found uncertainties relate to dynamic and temporal goal-relevant variabilities in the driving situation, and in particular the ones related to interactions with other traffic. There are only a few uncertainties that are spatial and/or more static by nature, such as those related to prevailing speed limit, nature of the intersections (equal or not), holes or objects on the road, traffic lights, optimal driving lines, lengths of entrance ramps, and the sufficiency of space on the road to fit passing vehicles. The dynamic uncertainties represent time-critical information requirements in driving whereas the static uncertainties are related to information requirements of the infrastructure of the traffic system (Kircher and Ahlström, 2017). The data suggests that most of these requirements in driving may be dynamic and time-critical, which is understandable for a dynamic visual-spatial tracking task.

From a methodical perspective, it is important to notice that anticipation is always a mental content. It is possible to anticipate only if people are able to represent the present and the possible future states of the situation in their minds. Chess players, for example, simulate possible future states in their minds when they search for the best move (Saariluoma, 1995). They generate and relate moves that are not present in their perceptual field, and thus, they can anticipate the possible courses of actions in their mental representations. The contents of their thoughts explain why they can represent future state of affairs and anticipate what will happen. Similarly, in the presented thinking-aloud protocol drivers generate future state of affairs and anticipate possible future courses of actions and the uncertainties of these. They mentally simulate what can happen and how they should act in a given situation to avoid negative outcomes of actions. The human ability to represent mental contents – that are often conceptual or qualitative – is decisive for the human way of anticipating possible future courses of events and to adapt their present actions to avoid accidents. How to enable this kind of generic capacity for automated vehicles without introducing computationally heavy world models is a challenging question. However, it seems that in order to improve the safety of automated driving to a human expert level – or beyond, this capacity is a requirement.

4.3.1 Limitations and future work

According to Lake et al. (2017), due to nonexistent world models, automated driving technologies cannot raise, for instance, the uncertainty about recognizing other road users' intentions or sufficient visibility. Based on the assumption of non-existing world models, the reviewed literature and the information publicly available online (e.g., https://www.tesla.com), some of the uncertainties in Tables 3 and 4 may be impossible to be recognized by current automated driving technologies. These uncertainties may remain out of reach of automated driving technologies for the distant future unless there are major advances made towards general artificial intelligence (Kujala and Saariluoma, 2018). However, the details of the state-of-the-art and developing commercial technologies outside academic knowledge are hard to find due to trade secrets. The authors are not experts in the engineering of automated driving technologies, and will not speculate which of the found uncertainties could or could not be recognized and/or resolved with current technology. We will leave this analysis for the domain experts and as a topic for further research. However, we believe this data is valuable for the developers in assessing the limitations of current state-of-the-art technology and in finding ways to improve situation awareness of future automated driving solutions. The introduced method and produced data can be utilized also for making automated vehicles to recognize such upcoming situations, in which the human should take over the vehicle, to enable timely take-over requests before safety-critical situations realize (Hecker et al., 2018).

On the other hand, many of the found uncertainties are probably not recognized by current automated driving technologies but could perhaps be recognized and resolved by the existing technologies. From a mimetic design perspective (Kujala and Saariluoma, 2018; Saariluoma et al., 2018), these are the most interesting uncertainties. With improved map data (e.g., Are road constructions causing exceptions in traffic arrangements?), machine vision (e.g., Do I hit the pothole/object on the road?), vehicle-to-vehicle and vehicle-to-infrastructure communications (e.g., Are traffic lights going to change?), and data fusion (e.g., If needed, is there space to yield to the adjacent lane?), many of these anticipatory capacities may possibly be implemented in today's or tomorrow's automated driving technologies. Further research should take each one of these uncertainties and create means for automated driving technologies to recognize and resolve these – if not yet being implemented.

The sample of driving instructors was quite small, although it seemed there was a saturation of data for the selected routes. As there was no direct control over the traffic conditions that is possible in a driving simulator, some of the situations were rare but still safety-relevant. With a larger sample, more of these events and possibly also other types of uncertainties could have been observed. Intuitively, all the found uncertainties seem to be such that these could be relevant across various traffic environments and cultures. However, the route was relatively short (57.2 km) and represented only the uncertainties relevant in the selected local traffic conditions and time of day, and therefore uncertainties relevant in other traffic environments, conditions and times of day (e.g., night) could be missing. In further research, the method should be applied to various traffic environments and cultures in order to reveal all the possible relevant uncertainty subcategories that are not handled by automated driving solutions.

In future studies, utilizing eye-tracking and vehicle data together with the prospective thinking-aloud method could enable more detailed quantitative analyses of the adaptive actions to the expressed uncertainties, such as speed and headway adaptations (cf. Kircher and Ahlström, 2018). This level of analysis might enable computational models of human expert drivers' decision-making and adaptations in situations with the recognized uncertainties (cf. Hubmann et al., 2018; Meghjani et al., 2019; Portouli et al., 2019) that may be useful for implementing these in automated driving algorithms.

5 CONCLUSIONS

We have introduced the prospective thinking-aloud method for analyzing how expert drivers (driving instructors) think as well as the anticipations and uncertainties of expert drivers related to safe, economical, and comfortable driving. The expertise of the driving instructors was validated with a hazard prediction test. As expected, driving instructors were able to anticipate unfolding hazardous traffic situations by a better rate than the other participant groups and it seems that this prediction ability evolves with practice.

The results of the field study indicate that there may be uncertainties in traffic that are perhaps not recognized or resolved with current automated driving technology solutions. It remains unclear if a great number of training data and great processing power are sufficient for overcoming these challenges. If the ultimate goal of this development is to create a fully autonomous vehicle that can cope in any complex driving situation with human road users, especially the social side of automated driving should be better understood.

However, the method also revealed a number of significant uncertainties that may not be considered in the development of automated driving technologies, but which may be recognized and resolved with existing technologies. Further, the introduced method may serve in enabling automated driving technologies to predict its probable failure, in order to alert the driver to take control well ahead of the failure (Hecker et al., 2018).

These findings and methodical contributions can be utilized when studying expert drivers' anticipations in different contexts, prototypical traffic situations and maneuvers and their information requirements for safe driving (Kircher and Ahlström, 2017; 2018), and for developing better automated driving technology by indicating automated vehicles' potential limitations as compared to expert human drivers.

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