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Assessment of the cooperation between driver and vehicle automation: A framework

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ABSTRACT

As long as the human driver is responsible for part(s) of the driving task during automated driving, the driver and automated driving system are sharing the driving task. Such a shared task is characterized by shared control, in which cooperation between the driver and vehicle automation is essential. However, means to holistically assess the quality of this cooperation are currently lacking. This work addresses how cooperation between driver and vehicle automation can be operationalized and assessed to gain insight into the quality of the shared driving task. Quality indicators and measurement methods are identified across seven dimensions reflective of the quality of cooperation between driver and automation. Based on previous empirical and theoretical studies a total of 34 quality indicators are identified. The methods to measure these quality indicators fall into four categories: 1) Subjective (such as questionnaires); 2) behavioral (such as reaction times, steering response); 3) neurophysiological (such as heart rate and pupil size); and 4) heuristic evaluation. The result is a first step in the development of a framework for the quantitative assessment of cooperation in the shared driving task. Yet, important knowledge gaps remain. For instance, the exact contribution of each quality indicator and their exact interrelationship are currently unclear. Moreover, all quality indicators reflect a requirement that should be met. Further research is needed to define exactly when each requirement is met. Additionally, it should be established to what degree each measurement method can validly and reliably provide insight into their quality indicator. Therefore, to ultimately ensure valid and reliable application of the framework in practice, the framework should continue to be developed and improved upon in future work.

1. Introduction

During the transition to fully automated vehicles (SAE Level 5) an increasing part of the driving task will be automated. Yet, as long as the human driver is still responsible for some part(s) of the driving task it can be considered as a task that is shared by the driver and the automation. In such a shared task it is invaluable for safe operation to not only have insight into the capabilities and limitations of

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the individual parties, but also in the quality of their cooperation as a *joint cognitive system* (e.g. Woods & Hollnagel, 2006) or as team members (e.g. Lee et al., 2023). Quality of cooperation may better predict safe driving performance than the contribution of the individual parties both in situ during the shared driving task in traffic and in a controlled (experimental) setting such as in a driving simulator or on a test track. Yet, a framework for the evaluation of the quality of the cooperation between driver and automation in the shared driving task in practice is currently lacking. Current evaluation methods in the field of automated driving generally either focus on the automated system (EuroNCAP, 2018) or on the human driver (e.g. Endsley, 2018). Theoretical frameworks to facilitate cooperation between driver and automation have been proposed (e.g., Guo et al., 2010). Moreover, human machine interface design principles (e.g. Carsten & Martens, 2019; Naujoks et al., 2019b) and frameworks to aid design of automation (e.g. Marcano et al., 2021) have been proposed that acknowledge the importance of the interaction and cooperation between driver and automation. Yet, these theoretical frameworks and principles are not intended for evaluation of the cooperation. A framework consisting of practical requirements and criteria is needed to evaluate the cooperation between driver and automation both in controlled experimental settings and on the road. The current paper aims to examine how cooperation in the shared driving task can be operationalized and assessed to gain insight into the quality of the shared driving task. The current paper builds on a model for the cooperation between the driver and automation by Petermeijer et al. (2021). Before explaining this model in more detail, the theoretical foundation for the current papers' model, including the foundation for how the current paper considers cooperation and the shared driving task, will be discussed.

1.1. Background

Important insights regarding cooperation in the shared driving task can be gained from the literature in three specific domains: 1) shared control; 2) joint action; and 3) cognitive systems engineering. Literature on shared control (Abbink et al., 2018; Abbink & Mulder, 2010; Boink et al., 2014; Flemisch et al., 2019; Itoh et al., 2016; Mars et al., 2014) defines shared control as humans and machines performing the same dynamic task while controlling the same part of the dynamic environment. The human and the machine are continuously interacting in a perception–action cycle in which the variability over time due to actions of the human and/or the machine and the interplay with the environment in which they operate both play an important role.

Whereas the literature on shared control is specifically focused on human–machine interaction, the literature on joint action focusses on human–human interaction. Joint action is defined by Sebanz et al. (2006) as "any form of social interaction whereby two or more individuals coordinate their actions in space and time to bring about a change in the environment." The potential of human–human interaction research for gaining more insight into human–machine interaction has been recognized in the literature for over 20 years (e.g. Castelfranchi, 1998; Flemisch et al., 2019; Hoc, 2000). The way in which we can learn from interactions between humans is clearly explained in an example described by Flemisch et al. (2019) of two people carrying a table together. The two people each contribute to a part of the table's movement, causing the situation to evolve. This example can be taken even a step further, where an observer observes how the two people carry a table together. This observer can oversee the situation and provide suggestions for how the two people should move in carrying the table together. Flemisch et al. (2019) indicate that their example makes it clear that shared control and cooperation are not exclusive concepts, but are intertwined: The two people carrying the table share control and they cooperate with each other and with the observer. This implies that shared control and good cooperation are not mutually exclusive, but that the quality of cooperation is related to the quality of shared control. This applies not only to carrying a table together but also to the focus of the present study: the driving task performed jointly by a human and automation. It has been emphasized in the literature that a common frame of reference (COFOR) is of importance in this cooperation (Hoc, 2000). To maintain this shared frame of reference, the parties must have shared goals and plans but also a clear division of roles. When there is no clear division of roles issues can occur, for example related to confusion about who should take control at what times. In addition, for a COFOR it is also important that there is shared situational awareness and monitoring and evaluation of actions.

Despite some similarities, cooperation between humans and machines is different from cooperation exclusively between humans in important respects. For example, some knowledge that is generally shared between humans, is not necessarily shared between humans and machines. Humans have knowledge about what other humans can understand, while humans do not always know what a machine is able to understand (Harbers et al., 2012). Moreover, constraints in human–human interaction can arise from societal conditions such as language, while constraints in human–machine interactions are often of a technological nature (Haberland, 1999). Over time, however, the differences between constraints in human–human interaction and in human–machine interaction have become smaller and smaller. For example, issues related to waiting times (the time it takes for the machine to process input and provide an output) used to occur, which are now less of an issue, if at all. Human-human interaction and human–machine interaction is thus becoming increasingly similar, and therefore issues that apply in the interaction between humans also become increasingly meaningful for the interaction between humans and machines.

According to literature in the domain of cognitive systems engineering, the interaction between a human and a machine can only be understood when both parties are not considered in isolation but as a whole (Hollnagel & Woods, 1983). From this perspective different models have been proposed to provide insight into the performance of the system as a whole, of which the Contextual Control Model (COCOM) and the Extended Control Model (ECOM) (Hollnagel & Woods, 2005) have been especially influential (e.g. Feigh, 2011; Kontogiannis & Malakis, 2013; Lundberg & Johansson, 2020). COCOM is based on the idea that how a so-called joint system behaves in achieving its goals depends heavily on the context in which actions take place. Actions are affected by anticipation of and in response to events. COCOM is a cyclical model in which events and feedback from the environment are perceived by the human and incorporated into a current understanding of the situation which is then transformed into an action. The action has an impact on the environment whose events are again observed, which continues the cycle of perception-understanding-action continuously. External changes have an impact on the perceived environment and therefore the cycle can be affected by external changes. Hollnagel (2017) provides an example of how COCOM can be applied to a human driver controlling a vehicle. In this example the human has a certain understanding of the perceived current situation including expectations about the surrounding traffic and the performance of the vehicle. Based on this understanding the driver controls the vehicle, which results in a certain action of the vehicle on the road. The performed action and (unexpected) events are perceived by the driver. Based on the perceived information the driver adjusts his/her understanding of the current situation and the whole cycle continues again.

ECOM (Hollnagel & Woods, 2005) takes COCOM a step further by repeating the single cycle from COCOM resulting in multiple cycles to reflect the different levels at which actions can be expressed and that could take place simultaneously. Returning to the example of the application of COCOM to human driving: An addition to this by ECOM would be that the driver automatically performs certain activities such as keeping distance from other traffic and adjusting the lateral position on the road. These automatic activities do not need much attention from the driver. In parallel, non-automatic activities are performed that do require attention such as monitoring traffic signals and adjusting goals and behavior based on this.

Lundberg & Johansson (2020) present a joint control framework based on ECOM and COCOM and other insights from cognitive systems engineering. In contrast to ECOM and COCOM, the joint action is central in the joint control framework. Additionally, the framework focuses specifically on the interaction between human and automated system. In this framework, a human and an automated system are included in one cycle, highlighting the importance of processes that are shared by the human and the automation. The cycle shared by human and automation has three important points: 1) a perception point, where the current state of affairs in

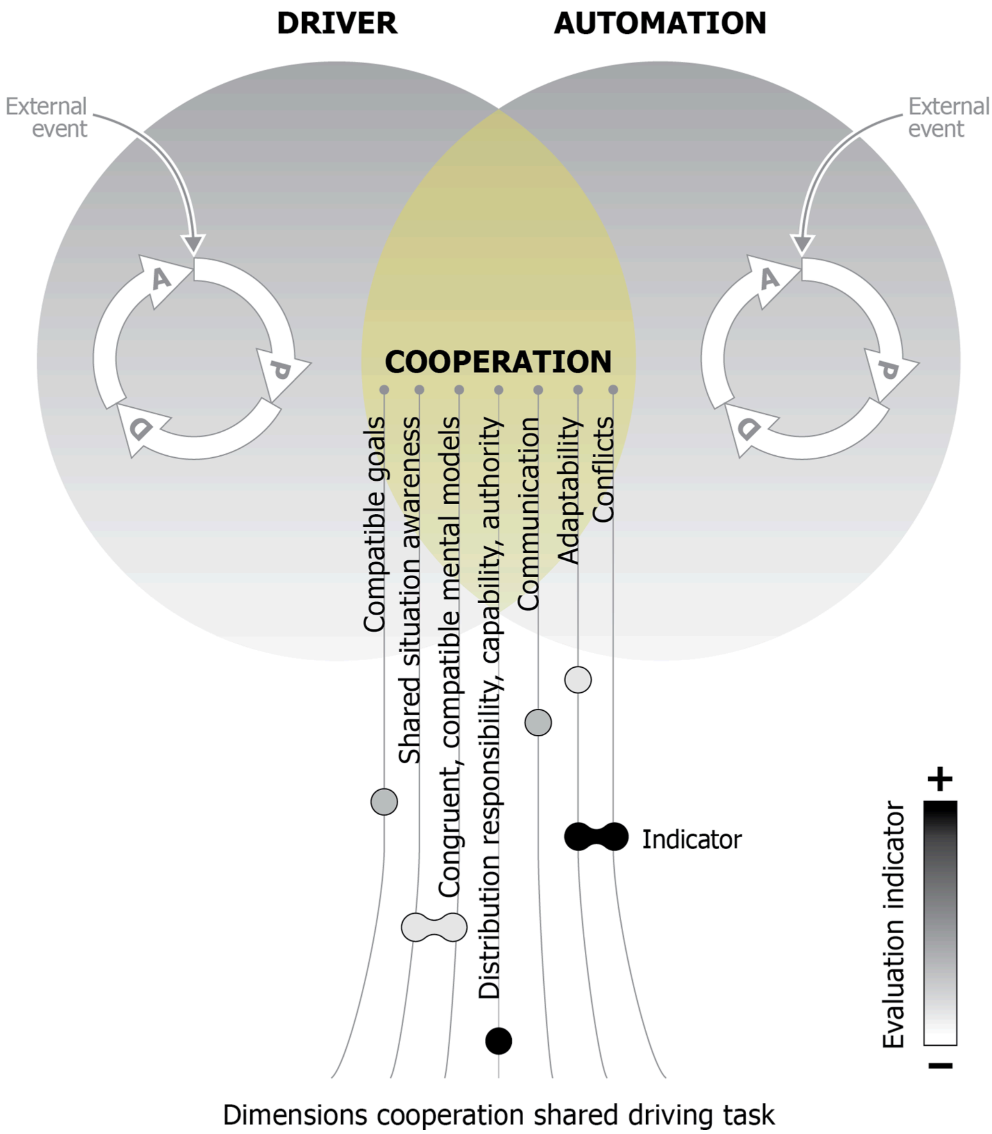

Fig. 1. Model for the Cooperation Between Driver and Automation in the Shared Driving Task. Adapted from Petermeijer et al. (2021). Note. P = perception, D = decision, A = action. See text for further details.

relation to the environment is observed, including external changes; 2) a decision point, where it is decided which actions should be performed; and 3) an action point, where actions are carried out. Lundberg & Johansson (2020) indicate that human and automation each are going through a cycle of perception-decision-action at different levels of cognitive control (from overarching goals to specific procedures and actions) and that important episodes, or joints, take place whenever the cycles of the human and the automation overlap.

In our previous work (Petermeijer et al., 2021) a literature survey and 3 focus group sessions with 15 experts in the field of automated driving (including experts from car manufacturers, academia and safety institutes) were conducted. Based on the literature survey and expert input, a model for the cooperation between the driver and automation was presented and seven dimensions were identified that are indicative for the quality of the cooperation. The model is presented in Fig. 1. In the model the driver and automation are depicted in the larger left and larger right circle, respectively. The driver and automation both go through a perception-decision-action cycle as depicted in the two smaller circles including three arrows: 1) The perception-arrow (P); 2) the decision-arrow (D); and 3) the action-arrow (A). Moreover, there is overlap between the driver and the automation (this overlap is colored in the figure), which indicates that there is an overlap between the cycles that the driver and the automation go through. In this overlap cooperation takes place. Note that the perception-decision-action cycle is similar to the one proposed by Lundberg and Johansson (2020), yet the model of Petermeijer et al. (2021) is focused specifically on cooperation, whereas Lundberg and Johansson (2020) focus on the interaction in general.

The quality of the cooperation between the driver and the automation is thought to be captured by seven dimensions following Petermeijer et al. (2021): 1) Compatible goals; 2) shared situational awareness; 3) congruent and compatible mental models; 4) distribution of responsibility, capability and authority; 5) communication; 6) adaptability; and 7) conflicts. These dimensions are focused on aspects that apply to both agents or that are shared by both agents. Several of the terms are typically used to describe characteristics of humans. Here they are also used for the automation in order to fully capture the cooperation between driver and automation. In the dimension ‘congruent and compatible mental models’, for example, the concept of ‘mental model’ is usually applied to describe the human’s understanding about the automation. In this case, this concept is also extended to the automation to indicate that it is also important that the automation has an understanding about the human. The dimensions are represented in Fig. 1 by vertical lines running down from the colored overlapping part representative of the cooperation. The idea is that each dimension can have several quality indicators that provide insight into the quality of cooperation within the shared driving task. In the figure, indicators are illustrated by dots on the dimensions. Because dimensions are probably not completely independent of each other, indicators can relate to multiple dimensions. Each indicator should be measurable in order to be able to evaluate the dimension(s) in which the indicator provides insight. Although Petermeijer et al. (2021) present the notion of using quality indicators to evaluate the seven dimensions that are indicative of the cooperation between the driver and the automation in the shared driving task, the indicators and how they could be measured are not specified.

1.2. *The current study*

In the current study we expand the model of Petermeijer et al. (2021) to set the next step towards developing a practical framework. Based on the literature we will define quality indicators for each of the seven dimensions and we will identify dependent variables and measurement methods in order to quantify the quality indicators. Identifying these quality indicators and measurement methods is an important next step towards being able to evaluate the quality of cooperation in the shared driving task in practice. Yet, the framework should continue to be developed and improved upon in future work. We will detail which essential questions should be addressed in future research.

2. Quality indicators and measurement methods

This section describes each dimension in more detail and presents quality indicators and associated measurement methods for each

Table 1
Quality Indicators, Dependent Variables and Measurement Methods for the Dimension ‘Compatible Goals’.

Quality indicator	Dependent variables	Measurement methods
Operational goals of the driver and automation are compatible	Discrepancy between the input of the driver and the automation	Steering and accelerator or brake pedal input differences (e.g. difference between the current steering angle of the driver and the automation)
		Questionnaires, interviews
	Adjustments or cancelations of a maneuver or de-activating the automation	Input provided by the driver through a human machine interface
Tactical goals of the driver and automation are compatible	Discrepancy between the driver and the automation	Questionnaires, interviews
	Adjustments or cancelations of a maneuver or de-activating the automation	Input provided by the driver through a human machine interface
Tactical goals are being mutually communicated	Percentage of tactical goals that are being communicated	Input to and output from a human machine interface combined and observations

dimension of the cooperation between driver and automation in the shared driving task. This section is divided in seven subsections, one for each dimension. Each subsection first explains the dimension and then presents the indicators and associated dependent variables and measurement methods to provide insight into the dimension. The resulting indicators, dependent variables and measurement methods are summarized in Tables 1 – 7.

2.1. Compatible goals

Both driver and automation have certain (programmed) goals in relation to the driving task. Those goals should be compatible (Flemisch et al., 2019) or positively interfering (Hoc et al., 2006) for good cooperation, meaning that goals of the driver and the automation do not have to match exactly, but should be compatible and not negatively interfering.

For the dynamic driving task both operational (basic vehicle control) and tactical (planning and execution for event/object avoidance and expedited route following) tasks are of importance (Michon, 1985; Society of Automotive Engineers International J3016, 2018), meaning that goals should be defined by the driver and automation for both types of tasks. When aiming to assess the compatibility of goals it is beneficial to establish how incompatible goals for both types of tasks manifest themselves. Incompatible goals for operational tasks can result in a discrepancy between the input of the driver and the automation in terms of steering and accelerator or brake pedal input (Abbink et al., 2019). For example, a difference between the current steering angle of the driver and the calculated steering angle of the automation could be an indication of a discrepancy in steering intentions. Note that a discrepancy that manifests itself on an operational level could potentially be the result of an incompatible goal on a tactical level. For example, the driver might want to overtake a vehicle while the automation does not want to change lanes (e.g., lane keeping assistance system). Large discrepancies between driver and automation input indicate incompatible operational goals, potentially originating from incompatible tactical goals, and may even lead to conflicts (more details on conflicts can be found in subsection 2.6). Small discrepancies are unlikely to be the result of incompatible goals, but may indicate a difference in preference or approach. Whether an intention difference is large or small depends on many factors, such as the traffic situation or driving environment.

Goals on a tactical level should be mutually communicated to prevent discrepancies on an operational level (more details on communication can be found in subsection 2.7). For example, if the automation decides to overtake a vehicle, this intention will have to be made clear to the driver. Similarly, a driver can for example let the automation 'know' that s/he intends to change lanes – by for example using the indicators – to ensure the lane keeping assistance system does not hinder this. To evaluate whether tactical goals are communicated, the percentage of tactical goals that are communicated from the tactical goals that should have been communicated can be measured through the human machine interface and observations.

When the driver does not agree with a maneuver that is planned by the automation, s/he should be able to adjust or cancel the planned maneuver or even de-activate the automation if it would still lead to a safe traffic situation. The input provided by the driver for adjusting or canceling a maneuver or de-activating the automation can be indicative of incompatible goals.

There are several complexities associated with gaining insight into compatibility of goals. When goals do not (yet) manifest themselves physically, compatibility has to be measured indirectly. Moreover, measured outcomes are not always unambiguous. For instance, disabling automation does not necessarily indicate problematic incompatible goals as it can also be possible that the driver simply has a preference to drive him- or herself. A combination of objective and qualitative measurement methods, such as questionnaires or interviews providing insight into possible intention differences, might therefore be needed to validly and reliably assess whether goals are compatible.

The quality indicators, dependent variables and measurement methods resulting from the above are summarized in Table 1.

2.2. Shared situational awareness

In order to be able to cooperate well, driver and automation should have shared adequate knowledge about the driving environment, which is also called situational awareness. Shared situational awareness reduces unexpected situations and their potentially

Table 2
Quality Indicators, Dependent Variables and Measurement Methods for the Dimension 'Shared situational awareness'.

Quality indicator	Dependent variables	Measurement methods
The driver perceives task-relevant cues	Visual attention	Eye tracking
The driver interprets task-relevant cues correctly	Degree to which behavior is suitable for current situation	Observations
The driver adequately predicts the development of future traffic situations, including potential hazards	Degree to which anticipatory behavior is suitable	Observations
	Visual attention to potential hazards	Eye tracking
The automation perceives task-relevant cues	Perception capability automation	Reading out automation's perception data
	Degree to which perception capabilities comply to design principles	Heuristic evaluation
The automation interprets task-relevant cues correctly	Degree to which behavior is suitable for current situation	Observations, reading out data of the automation
The automation adequately predicts the development of future traffic situations, including potential hazards	Degree to which anticipatory behavior is suitable	Observations, reading out data of the automation

Table 3
Quality Indicators, Dependent Variables and Measurement Methods for the Dimension 'Congruent and compatible mental models'.

Quality indicator	Dependent variables	Measurement methods
The driver understands the functioning of the automation	Understanding about the functioning of the automation	Questionnaires, interviews
The driver has an appropriate mode awareness and mode confusion should be prevented	Mode awareness	Questionnaires, interviews
	Relational attention ratio	Eye tracking combined with questionnaires, interviews
	Behavior and driving performance (including mode errors)	Observations
The driver's trust/reliance in the automation aligns with the functional capabilities of the automation	Trust/reliance	Questionnaires, interviews
	Behavior (including disabling the automation)	Observations, reaction times
	Monitoring behavior	Eye tracking
	Driver state	Neurophysiological measures
The driver is able to predict the behavior of the automation in response to the situation	Anticipatory behavior	Observations
The automation takes into account general human factors principles	Degree to which the system and it's code comply with human factors principles	Heuristic evaluation
The automation has insight into the (upcoming) state of the driver and the characteristics of the driver	Degree to which the estimated state and characteristics of the driver match the actual driver's state and characteristics	Comparing estimations against a ground truth
The automation communicates clearly about the state of the automation (see subsection 2.5 for more details)	See subsection 2.5	See subsection 2.5

Table 4
Quality Indicators, Dependent Variables and Measurement Methods for the Dimension 'Distribution of responsibility, capability, and authority'.

Quality indicator	Dependent variables	Measurement methods
The driver's responsibility does not exceed his/her authority and capability	Degree to which the driver's behavior is appropriate for the level of responsibility	Lane deviation, lane crossings, abrupt braking, reaction times, observations
	Degree to which the driver's state is appropriate for the level of responsibility	Neurophysiological measurements, questionnaires, peripheral detection/response task
The driver's authority does not exceed his/her capability	Degree to which the driver's behavior is appropriate for the level of authority	Lane deviation, lane crossings, abrupt braking, reaction times, observations
	Degree to which the driver's state is appropriate for the level of authority	Neurophysiological measurements, questionnaires, peripheral detection/response task
The automation's responsibility does not exceed its authority and capability	Degree to which the automation is adequately programmed, including the right rules	Heuristic evaluation

Table 5
Quality Indicators, Dependent Variables and Measurement Methods for the Dimension 'Communication'.

Quality indicator	Dependent variables	Measurement methods
All information the driver needs about the automation is communicated to the driver	Degree to which the necessary information is being communicated	Heuristic evaluation
All information the automation needs about the driver is communicated to the automation	Degree to which the necessary information is being communicated	Heuristic evaluation
Information communicated about the automation to the driver is correct	Degree to which the communicated information is correct	Comparing communicated information against a ground truth
Information communicated about the driver to the automation is correct	Degree to which the communicated information is correct	Comparing communicated information against a ground truth
Communicated information is understood well by the driver	Comprehension	Questionnaires, observations
Communicated information is understood well by the automation	Degree to which the information is processed well	Reading out data of the automation, observations
Communication supports the other dimensions	See the subsections on the other dimensions	See the subsections on the other dimensions
Communicated information does not distract and does not induce information overload in the driver	Information load (in relation to the context including the current driver responsibilities)	Questionnaires, neurophysiology, peripheral detection task or response task
Communicated information is usable for the driver	Usability	Questionnaires
The driver intends to use the communicated information	Acceptance	Questionnaires
Communicated information has the right impact on the automation	Degree to which the automation adequately uses the communicated information	Heuristic evaluation

Table 6
Quality Indicators, Dependent Variables and Measurement Methods for the Dimension 'Adaptability'.

Quality indicator	Dependent variables	Measurement methods
The driver needs to adapt to the automation and to the driving environment	Response to unexpected situations	Observations, reaction times, steering response, eye tracking, time-to-collision
	Anticipation	See subsection 2.2 and 2.3
The automation needs to adapt to the driver and to the driving environment	Response to unexpected situations	Reading out data of the automation, observations
	Anticipation	See subsection 2.2 and 2.3

Table 7
Quality Indicators, Dependent Variables and Measurement Methods for the Dimension 'Conflicts'.

Quality indicator	Dependent variables	Measurement methods
Conflicts are minimized	Number of conflicts	Observations
	Degree of compatibility between input and output of the driver with input and output of the automation	Input to and output from a human machine interface/the automation combined and observations
	Irritation	Questionnaires
When a conflict occurs, it is resolved adequately	Quality of correction and transfer in driver	Number and time of needed actions, heuristic evaluation, time to collision, longitudinal and lateral acceleration, time to lane crossing
	Whether the conflict is solved	Observations
	Increase in driver fitness in response to corrective action	Neurophysiological measures, observations

negative consequences. Each agent should have situational awareness required for its tasks (Endsley, 1995). Situational awareness of each individual agent can be combined and can be shared in order to reach a shared situational awareness (McNeese et al., 2021). Three aspects are crucial for both driver and automation to ensure adequate shared situational awareness: 1) Perceive task-relevant cues from the changing driving environment; 2) interpret the cues correctly and 3) make appropriate predictions about the future state of the cues (Endsley, 2006; Endsley, 1995; Merat et al., 2019). Exactly which environmental elements are task-relevant for shared situational awareness depends, among other things, on the task and the responsibility distribution (also see subsection 2.4). If driver and automation share the same task (for example, an operational task such as steering), then the same elements are important to both. If the responsibility of a subtask lies entirely with the automation then the situational awareness of the driver may shift to elements that are currently only important to the driver. The degree of required shared situational awareness therefore also changes depending on the current mode.

Regarding perception of task-relevant cues in the driving environment, it is essential that both driver and automation perceive hazards when they share a task (Victor et al., 2018). Whether the driver perceives hazards and other task-relevant cues can be assessed by head and eye movements providing insight into visual attention (Liang et al., 2021). To determine whether the automation is perceiving properly can be assessed through verification of design requirements through heuristic methods and reading out the perception data and the code of the automation (Harbers et al., 2012). If both the driver and automation have perceived all relevant elements then it can be said that they share situational awareness on a perception level.

In addition to perceiving relevant cues, it is also important that those cues are correctly interpreted (Victor et al., 2018). Whether the driver correctly interprets these task-relevant cues is difficult to determine with current objective measurement methods. Attempts have been made to gain insight into interpretation using methods that measure brain activity - such as EEG (Kästle et al., 2021) and fNIRS or functional near-infrared spectroscopy (Hirshfield et al., 2015) - but these methods do not provide direct insight into whether a situation is correctly interpreted. Body posture and hand movements can, through expert observation or through observation of camera images, give an indication of correct interpretation of relevant cues in relation to the environment (Trivedi & Cheng, 2007). In addition, the actions of the driver and of the automation could also be examined (McNeese et al., 2021); if these are appropriate for the current situation and match each other then this also indicates a good interpretation of the cues. The actions can be measured through observations or camera images and data from the automation.

Adequate prediction of the cues in the driving environment based on the perception and interpretation of the cues is a prerequisite for potential hazard recognition (Crundall, 2016). Potential hazard recognition can manifest itself in anticipatory behavior in both the driver and the automation. For example, when a driver interrupts a non-driving-related activity when the automated vehicle reaches a stretch of highway with road works, even when the vehicle automation has previously handled this situation without issues. There have also been attempts to assess potential hazard, or latent hazard (Vlakveld et al., 2018), recognition in traffic by measuring whether drivers are looking in directions in which a potential hazard might occur while it is not currently visible (e.g., the possibility of another vehicle coming from a side street). Whether the automation takes into account potential hazards can be assessed by measuring the appropriateness of the automation's prediction data and the automation's behavior in traffic.

Table 2 summarizes the quality indicators, dependent variables and measurement methods resulting from the above.

2.3. Congruent and compatible mental models

The term 'mental model' is mostly used in the literature (Banks et al., 2018; Norman, 1983; Merat et al., 2019; Kurpiers et al., 2019) to refer to the human's knowledge about the limits and functioning of the automation. In the current work we also use the term to refer to the automation's understanding about the human's limits and how the human driver is functioning. The automation implicitly has, through the way it is designed, a 'mental' model of the human partner that it cooperates with (Flemisch et al., 2012). This mental model is built into the code as an inherent part of the system. In order to cooperate well, the mental models of the driver and the automation must be generally congruent and compatible (Flemisch et al., 2012).

A congruent and compatible mental model makes it possible for the human driver to apply past experiences of cooperation to new situations. In this way, mental models contribute to the predictive aspect of situational awareness (see subsection 2.2 on shared situational awareness). For example: If a driver has learned from previous experience that the automation has difficulty functioning when there are temporary road markings for road works, the driver can prepare to take over control. The driver's mental model about the automation allows to predict the automation might fail under these circumstances. The degree to which the driver can correctly predict the functioning of the automation given the circumstances, and, more generally, the understanding of the functioning of the automation can therefore provide insight into the mental model the driver has about the automation. The driver's understanding of the automation's functioning can be assessed through structured interviews, as used for example by Sarter et al. (2007) and Forster et al. (2019b). Whether predictions of the automation's functioning are correct can be tested by looking at the driver's anticipatory behavior. Anticipatory behavior can be measured by means of observations. For example, Lindgren et al. (2020) applied drive-along observations in a research car (SAE Level 3 and simulated SAE Level 4) during commutes of participants. During such a drive-along the participant was in the driver's seat and a researcher sat in the back seat. Participants were provided the opportunity to ask questions and to interact with the researcher. Questions and interactions were for a part driven by the participants' anticipation and expectations. Video recordings were made during the drive-along. These recordings were transcribed and quotes related to anticipation were identified, coded and analyzed.

A driver's mental model can be supported by mode awareness, which entails the driver being aware about the currently activated automation mode and the associated capabilities (Kurpiers et al., 2020; Sarter et al., 2007). The opposite of mode awareness is mode confusion, which refers to confusion about the activated automation mode and its associated capabilities (Sarter & Woods, 1995). Mode confusion occurs, according to Bredereke & Lankenau (2002), when the behavior of the automation is incongruent with the driver's expectations arising from the driver's mental model. Mode confusion can be dangerous because it can lead to incorrect actions from the driver, which are also called mode errors (Sarter & Woods, 1995). The degree of mode awareness/mode confusion and associated mode errors therefore also provides insight into the accuracy of the driver's mental model. Kurpiers et al. (2020) describe in detail how to best measure mode awareness and suggest combining measures of driver knowledge and behavior. They propose to measure knowledge by means of a questionnaire about the understanding of the automation and to measure behavior by means of the 'relational attention ratio'. This ratio is the percentage of time the driver is looking at a region of interest. Areas of interest are for example the middle of the road just below the horizon, the instrument panel, the side mirrors and the rear view mirror. However, there is not always a one-to-one relationship between time spent looking at these regions and whether attention is actually paid to these regions. In addition, it is not only important that the driver notices important aspects in traffic, but also whether the driver actually acts when necessary (Victor et al., 2018). Certain patterns in the driving performance and behavior of the driver can be a sign of mode confusion. For example, the driver might keep holding on to the steering wheel when it is not necessary to do so in the current mode or the driver might push buttons randomly, or might show facial expressions of confusion. Such behavioral observations should be verified by reports of the driver's understanding to determine whether the behavior was actually the result of mode confusion (Kurpiers et al., 2020). Therefore, combining measures of the driver's knowledge and understanding, the relational attention ratio and observations of behavior seems to be a promising combination for testing driver's mode awareness and the corresponding knowledge on limits and boundaries of the automation. Mode awareness, and therefore the driver's mental model can be supported by clear communication on the automation's current mode and limitations (see subsection 2.5 on communication).

The mental model of the driver is closely related to the driver's trust in the automation, or the expectation that the automation will help achieve the driver's goal even in uncertain situations (Lee & See, 2004). It is important that the level of trust matches the functional capabilities of the automation. This match is more likely if the driver has an accurate mental model about the automation and thus understands these capabilities, including the limitations. Such an accurate alignment of trust is also called calibrated trust (Lee & See, 2004). Without calibrated trust there can be either overreliance or underreliance, in which the driver relies too excessively on the automation or is not inclined to rely on the automation, respectively. Trust and (over/under)reliance can be assessed through interviews or questionnaires, such as the Automation Trust Scale (Jian, et al., 2000) or the Automation-Induced Complacency Scale (Merritt et al., 2019). Moreover, behavior of the driver can provide important insights. For instance, frequently disabling the automation at times when it could be used reliably can be indicative of underreliance (Parasuraman & Riley, 1997). Yet, as noted before, a driver can also turn off the automation for the pleasure of driving manually. Additionally, reaction times have been applied to gain insight into trust (Payre et al., 2016) and measures of viewing behavior can provide insight into whether the driver is adequately monitoring the driving environment when needed (Hergeth et al., 2016). Note, however, that adequate monitoring does not necessarily mean that the driver realizes when it is needed to intervene (Victor et al., 2018). Assessment of the appropriateness of the driver state, through for example neurophysiological measures (such as brain activity, heart rate, heart rate variability, skin conductance, respiration and pupil size), could also provide insight into reliance. For example, engagement in a secondary task leading to distraction when the reliability of the automation does not allow for it might also be indicative of overreliance. Again, when assessing trust or reliance, it appears to be valuable to combine different types of measures (e.g. questionnaires combined with observations of behavior) to ensure valid assessment.

Regarding the automation's mental model of the driver, the automation should be programmed in such a way that important general human factor principles (e.g. Carsten & Martens, 2019; Naujoks et al., 2019b) are taken into account. Moreover, the automation should understand the intention of the driver and predict his/her future behavior (Schneemann & Diederichs, 2019). Data on the dynamic driver's state can be collected and analyzed to gain insight into the driver's dynamic functioning. It is especially important that driver inattention, including distraction and fatigue, is taken into account by the automation as driver inattention is a major factor in most traffic accidents (Dong et al., 2011). Moreover, data providing insight into the driver's preferences and comfort, such as preferred driving style and when the driver is likely to turn the automation on or off, is also important for the automation when constructing a mental model of the driver. The extent to which the automation's built-in mental model is in line with human factors principles can be tested by checking whether the system and its code comply with the principles, for example by assessing the system and the code using a heuristic evaluation (following for example methodology as described in Forster et al., 2019a and Naujoks et al., 2019a). The accuracy of the automation's non-inherent mental model about the driver can be assessed by comparing the state and preferences of the driver as estimated by the automation to a ground truth. A ground truth can be established through subjective report measures, neurophysiological measures, physical measures, driving performance measures, or a combination of these measures (Dong et al., 2011). Especially a combination of these measures is thought to provide more reliable results (Dong et al., 2011).

There should not only be congruency and compatibility in the mental models of driver and automation regarding the partner's functional capabilities and limitations, it is also of importance that both partners have a clear 'understanding' about the distribution of responsibility and authority (Flemisch et al., 2012). This distribution should be in line with the capabilities of both partners. For more information see subsection 2.4.

The quality indicators, dependent variables and measurement methods relating to congruent and compatible mental models are summarized in Table 3.

2.4. Distribution of responsibility, capability, and authority

A well-balanced distribution of responsibility, capability and authority between a human and a machine is important for good human–machine cooperation as highlighted by Flemisch et al. (2012). Here we apply the notion of Flemisch et al. (2012) to the context of driver-automation cooperation within the shared driving task. In this context, responsibility can be defined as the extent to which the successful or unsuccessful completion of a (sub)task, as well as its consequences, are attributed to the driver and/or automation. Capability refers to having the necessary skills and resources (e.g., time, processing power) to perform the assigned (sub)tasks. Authority can be defined as what the driver and/or automation are allowed to do or not to do. It includes the authority to give more or less control to the other agent. Responsibility, capability and authority cannot be considered in isolation, but are closely related: An agent's responsibility should never exceed his authority. Likewise, an agent's authority should never be greater than his capability. It follows logically that responsibility should also never be greater than capability.

For adequate cooperation, (sub)tasks should be distributed in such a way that the responsibilities, capabilities, and authority of humans and automation complement each other (Flemisch et al., 2012). For example, when only the Adaptive Cruise Control function is activated (SAE Level 1) the automation is responsible and authorized (by the driver) for longitudinal vehicle control, whereas the driver is responsible for lateral vehicle control and monitoring the driving environment (since this would exceed the capability of the automation in absence of a lane keeping assistance system). If the ability of the driver changes, because of distraction, for example, such mutual complementation of responsibilities will no longer take place, which will eventually lead to dangerous driving behavior (deviating from the lane, jerky steering movements to correct, etc.). Objective measures of driving behavior, such as lane departure standard deviation, lane crossings, abrupt braking behavior, can therefore provide insight into the quality of cooperation with respect to this particular aspect.

Furthermore, responsibility, capability and authority must be balanced at all times within a dynamic driving environment that can change in an instant. For example, when humans experience underload due to their responsibility being limited to passive monitoring, a sudden change in the driving situation, e.g. due to an accident, may require a redistribution of authority and responsibility. In the case of inadequate cooperation, the sudden increase in workload may lead to a situation in which the driver's responsibility temporarily exceeds his/her ability to perform a critical maneuver in a timely manner. Again, driving performance, such as reaction time to a critical event, can provide insight into whether the dynamic balance between responsibility, capability and authority is appropriate. In addition, cognitive load of the driver can be measured using objective neurophysiological methods, using subjective methods (such as questionnaires, e.g., NASA-TLX [Hart & Staveland, 1988]), and/or using a peripheral detection task or response task (see, e.g., Patten et al., 2006; Chang et al., 2017). The idea is that when these measures indicate the driver to be underloaded or overloaded that there can be an issue in the distribution of responsibility, capability and authority.

Especially in the case of highly automated vehicles that reduce the driver's role to that of a supervisor, underload can be problematic (Cabrall et al., 2019; Merat et al., 2012). Drivers may become distracted or engage in non-driving related tasks, which can result in neglect of the supervisory role. Therefore, measurements that provide insight into whether drivers are dedicated to their assigned tasks can also provide insight into whether the distribution of responsibility, capability and authority is appropriate. For example, eye tracking can be used to determine the extent to which the driver fixates task-relevant areas, such as the road or certain displays (e.g., de Winter et al., 2019; Stapel et al., 2020; Zhou et al., 2021). The position of the head and general body posture, as well as NDRA engagement, can also provide insight into the driver's level of attentiveness (e.g., Doshi & Trivedi, 2012; Ohn-Bar et al., 2014). According to UN regulations on automated lane keeping systems (UNECE, 2020) the driver is only deemed available and able to respond to a transition demand when at least two availability criteria (e.g. driver input to the vehicle, eye blinking, eye closure and head or body movements) are met in the last 30 s. The regulation highlights the importance of combining multiple measurement methods and also providing an indication of an appropriate time window to consider for these measurements, at least in the case of automated lane keeping.

Since authority and responsibility (as well as capability) of the automation are defined in the design, the automation can be thoroughly tested a priori to determine if it is adequately programmed, including whether the right rules have been included. These rules, however, are not yet known and have yet to be established.

Table 4 summarizes the quality indicators, dependent variables and measurement methods resulting from the above.

2.5. Communication

Flemisch et al. (2019) considers communication between human and automation as an overarching aspect that occurs at all task levels of cooperation. To ensure adequate cooperation, it is important that 1) the necessary information is being communicated, 2) the information is correct, 3) the information is understood and 4) the information has impact.

It is valuable to consider the needs of both agents when determining what information is communicated in order to ensure communication at the right time with the right information (Alshehri et al., 2019; McNeese et al., 2021). To assess whether the necessary information is being communicated from driver to automation and from automation to driver a heuristic evaluation (e.g., checklist) taking into account guidelines can be used. These guidelines are currently being developed. For example in the Horizon 2020 research project 'MEDIATOR' (No 814735) activities are taking place to determine what should be communicated through a human-centered HMI during different levels of automated driving. For example, the driver needs to receive information supporting supervision and self-regulation, which can be attained through communicating continuously on automation reliability and providing anticipatory information including the available time until a change in automation mode, information on the upcoming automation mode and reasons for switching to another automation mode (Tinga et al., 2022a). With regards to the 'information needs' of the automation, the automation needs to continuously have insight into the (upcoming) capabilities of the driver. For example, the automation needs to receive input on fatigue and distraction in order to build up a sufficient mental model of the driver (Borowsky et al., 2020; see also subsection 2.3 why this information is of importance).

If the necessary information is being communicated, it also should be assessed whether the communicated information is correct. In order to establish whether the automation receives correct input about the driver, on for example fatigue and distraction, the received input can be tested against a ground truth, a measurement method that we also explained in subsection 2.3. Ideally, the automation should be programmed in such a way that it always communicates the right information to the driver. Yet, the automation may be uncertain about estimated information, in that case the uncertainty should also clearly be communicated to the driver to ensure s/he can take the uncertainty into account. Exactly how this uncertainty should be communicated, however, is currently unclear. The correctness of the communicated information about the automation to the driver can be established as well by comparing the information against a ground truth.

The communicated information should additionally be understood well to ensure adequate cooperation. Communication must therefore be clear and unambiguous, to prevent misinterpretation of the message (Wickens et al., 2003). Whether communication is well understood by the driver can be measured by using questionnaires to test the driver's comprehension of the communicated information. Alternatively, the driver's behavioral response to the information can be assessed. If the driver's behaves incorrectly, then this might indicate misunderstanding of the information. In a similar way it can be tested whether the information from the driver is correctly processed by the automation by examining whether the information is correctly interpreted and responded to. When focusing on the response to the information, the focus is already shifted towards the impact of the communication.

Communication should have a positive impact on the other dimensions of the framework. This makes the dimension 'communication' inextricably linked to other dimensions. For example, communication should contribute to shared situational awareness and congruent and compatible mental models (e.g. McNeese et al., 2021) and should support the distribution of authority, power and responsibility. In addition, it should be ensured that communication is not distracting the driver from his/her responsibilities and does not lead to information overload. To provide an example of how to prevent information overload, pieces of available information can be provided at one time and/or information can be prioritized. Information load can be measured through questionnaires (e.g., NASA RTLX; Hart & Staveland, 1988) or through neurophysiological measurements. Another alternative to measure workload is by means of a peripheral detection task or response task (see for example Patten et al., 2006; Chang et al., 2017). The information load should be considered in combination with the cognitive load resulting from the current context, including the current driver responsibilities. To test whether the information can be used by the driver, one can examine usability through questionnaires (e.g. System Usability Scale; Brooke, 1986). In addition, acceptance can be assessed through questionnaires (e.g. Van der Laan Acceptance Questionnaire, Van der Laan, et al., 1997), which indicates whether the driver also intends to use the information. These measurements provide (partial) insight into whether the driver is indeed supported by the provided information. The impact of the communication on the automation should be right due to the design of the automation. If the right information is communicated to the automation and interpreted correctly then the information should have the right impact on the automation. Whether this is implemented correctly can be evaluated using a heuristic evaluation.

The quality indicators, dependent variables and measurement methods resulting from the above are summarized in Table 5.

2.6. Adaptability

The task to drive a car takes place in a complex dynamic context. Therefore, the cooperation between driver and automation requires adaptability from both agents, both to the driving environment but also to the other agent (Kolekar et al., 2020). For example, depending on the reliability of the automation the driver needs to adapt his/her take-over-readiness or level of attention. On the other hand, the automation should adapt to the state of the driver, for example by providing additional steering assistance when the driver is momentarily distracted (Flemisch et al., 2008). Especially when unexpected situations arise, adaptability is crucial to ensure cooperation does not degrade. For example, a fatal crash can occur when both automation and driver fail to brake when a pedestrian unexpectedly crosses the street, as happened in Arizona in 2018 (Stanton et al., 2019). A team that knows how to adapt quickly and well to each other and to the circumstances results in robust cooperation, in which unexpected situations are handled in a safe way (following CFR, 2021).

Adaptability is difficult to measure directly because it will only lead to a measurable action of the driver or automation in unexpected situations. In simulator experiments or on test tracks, such actions can be safely evaluated, e.g., by having the automation or driver deliberately fail (Petermeijer et al., 2015). Indicative objective measurement methods in such experiments to gain insight into adaptability of the driver include observations, reaction time, steering response, hazard recognition based on eye tracking, or time-to-collision (Louw et al., 2017; Petermeijer et al., 2015; Schömig et al., 2011; Stahl et al., 2019). To gain insight into adaptability of the automation in such experiments the data of the automation can be read out and/or the response of the automation can be observed. In addition, suitable anticipatory behavior of the driver and the automation (as also discussed in subsection 2.2 on 'shared situational awareness' and subsection 2.3 on 'congruent and compatible mental models') can also be indicative of adequate adaptability to the driving environment and to the other partner.

The quality indicators, dependent variables and measurement methods for the dimension 'adaptability' are summarized in Table 6.

2.7. Conflicts

A conflict occurs when the driver's input is not consistent with the automation's input (Itoh et al., 2016). Conflicts are strongly related to the dimension 'compatible goals' (see subsection 2.1), as incompatible goals might result in conflicts. If the goals of the automation and driver are compatible and if quality indicators for the other dimensions of the framework indicate adequate cooperation, it can be expected that conflicts will be minimized. Conflicts should be minimized as they can result in irritation in the driver, which can affect the use of a system (Abbink et al., 2019). Assessing the number of conflicts through observations and the degree to which input and output of both agent are compatible can provide insight into whether conflicts are minimized (McNeese et al., 2021). In addition, questionnaires can be applied to gain insight into whether irritation is occurring as a result of conflicts.

As long as the driving task is shared, however, conflicts can probably not be prevented completely. Moreover, a conflict is not always undesirable. In fact, conflicts can function as a form of communication as they can serve as warnings and can provide some insight into the limits of the capabilities of the other agent (Itoh et al., 2016). Yet, it is of importance that conflicts (especially more major ones) are properly communicated and handled to avoid critical errors (Itoh et al., 2016). The agent with the responsibility should have the authority to resolve the conflict. In the near future, the driver will continue to be the agent who is legally responsible for road safety (and thus the agent with authority as described in subsection 2.4). Thus, to ensure adequate conflict handling it is currently necessary that the driver has the possibility to correct actions of the automation or to switch off the automation completely. Correcting and disabling of the automation must be possible in a simple and intuitive way. Corrections and transfers of full control back to the driver can provide insight into how well (potentially occurring) conflicts can be handled by the driver, for example by measuring the number of actions and the time needed for corrections and/or a transfer of control. Alternatively or additionally, heuristic evaluations can identify whether the driver can easily correct or disable the automation. Moreover, the quality of the transfer can be measured through (a combination of) methods such as time to collision, longitudinal and lateral acceleration and time to lane crossing (Cleij et al., 2021). The automation should also correct the driver when needed, especially in case the automation will be granted more authority in the future. For example, when the driver does not take over control when required because the driver is inattentive, attention can be drawn by providing a pull force on the seatbelt. The impact of the corrective actions can be evaluated by examining the average increase in fitness in the driver as a response to the corrective action (Cleij et al., 2021).

Table 7 summarizes the quality indicators, dependent variables and measurement methods resulting from the above.

3. Discussion

The current paper examined how cooperation between a human driver and automation in the shared driving task can be assessed to gain insight into the quality of the shared driving task. We expanded on a framework described by Petermeijer et al. (2021) which includes seven dimensions thought to be reflective of the quality of the cooperation: 1) Compatible goals; 2) shared situational awareness; 3) congruent and compatible mental models; 4) distribution of responsibility, capability and authority; 5) communication; 6) adaptability; and 7) conflicts. Based on the literature, we identified 34 quality indicators that could provide insight into the dimensions. Moreover, we identified how these quality indicators can be measured. In this way, the current paper sets an important next step in developing a framework for the assessment of cooperation in the shared driving task. However, the framework should continue to be developed and improved in future work before the framework can be applied in practice. We will discuss the main outcomes of the current work and the recommended next steps in more detail below.

Regarding the identified quality indicators, each indicator provides insight into only part of a dimension. Therefore, multiple quality indicators should be considered. Note that it is possible to find opposing quality indicators (i.e., in terms of indicated adequateness) within a particular dimension. For example, one may find that conflicts are adequately minimized, but that when they occur they are inadequately resolved. Likewise, it is possible to find one dimension to be adequate while another is found to be inadequate. For example, one may find a cooperation between driver and automation with adequate 'shared situation awareness' but inadequate 'adaptability'. It is currently unclear whether all quality indicators and whether all dimensions should be rated as adequate to establish good quality cooperation, or whether certain quality indicators or dimensions can be rated as inadequate when all others are rated as adequate without having a detrimental effect on cooperation. As noted before, the dimensions overlap and are inextricably linked. For example, when there is inadequate communication this will ultimately also negatively affect other dimensions. Therefore, the exact contribution of each quality indicator and dimension and their interrelationship should be established in future work, ideally resulting in a parsimonious set of dimensions and quality indicators.

The quality indicators all reflect a requirement that should be met. However, it is not yet clear for most quality indicators how the requirement should be operationalized (e.g., how many conflicts indicate that conflicts are or are not minimized?). Moreover, environmental and contextual factors also play a role in the demands on the shared driving task, potentially affecting when a requirement is met. Therefore, criteria for the quality indicators might have to be dynamic, changing depending on the environment and context. This could for example be dealt with by developing algorithms taking environment and context into account. Before such algorithms can be developed, it should first be established in future work how criteria can best be determined (dynamically).

Regarding the identified measurement methods, these methods fall into four different categories: 1) Subjective (such as questionnaires); 2) behavioral (such as reaction times, steering response); 3) neurophysiological (brain activity, heart rate, heart rate variability, skin conductance, respiration, pupil size); and 4) heuristic evaluation (such as a checklist) and evaluation of correctness of data (such as a comparison against a ground truth). When considering these different types of measurement methods for the assessment of cooperation, the advantages and disadvantages of each type of method should be taken into account. For example, subjective and behavioral methods can be affected by the process of measurement in which a driver consciously or unconsciously adjusts his/her answers or behaviors, whereas neurophysiological measurement methods cannot be as easily affected by the driver (Page et al., 1966; Tinga et al., 2020). Neurophysiological measurements, on the other hand, are somewhat less specific, since they reflect different functions of the nervous system, affecting both the validity and reliability of these measurements (Tinga et al., 2020). The question that remains is to what degree each identified measurement method can validly and reliably provide insight into their quality indicator. For several constructs as part of the quality indicators it has been acknowledged that a combination of different measurement methods often gives the best insight (e.g., Kurpiers et al., 2020; UNECE, 2020; Victor et al., 2018).

Some measurement methods can almost only be applied post hoc (e.g., questionnaires). Therefore, if one wants to gain insight into the quality of cooperation in situ during the shared driving task in practice, these post hoc measurement methods are unsuitable. However, post hoc measurements are useful for evaluation in experimental settings. There are also a number of online (i.e., continuous, during the actual driving task) measurement methods that provide insight into processes during the shared driving task whose applicability on a large scale in traffic is currently a challenge. This is especially the case for neurophysiological measurement methods that are very sensitive to noise and/or whose equipment is very expensive. These methods currently seem to be better suited for evaluation in a more experimental setting. A promising neurophysiological method for measuring online during the shared driving task in traffic is eye tracking, as this method is successfully used in experiments and also in more naturalistic settings (e.g., Castritius et al., 2021; Liang et al., 2021; Victor et al., 2018). In such online measurements a time window that will be considered should be determined. For example, the UN regulations on automated lane keeping systems (UNECE, 2020) include the last 30 s when determining driver availability. Methods that measure behavior also seem to be suitable for application in situ. When using a combination of different methods, a more comprehensive insight might be provided, yet when this involves a combination of post hoc and online measurements, a complete online measurement is no longer possible.

The identified quality indicators and measurement methods to assess cooperation in the shared driving task are the result of connecting the results of empirical and theoretical studies. Experimentally testing (parts of) the framework will support in identifying what aspects of the framework should be improved upon in addition to the aspects addressed above, with the goal of ultimately ensuring valid and reliable application of the framework in practice. A roadmap to achieve structured evaluation of the cooperation between driver and automation in practice which builds on the framework has been defined (see Tinga et al., 2022b for details which also includes a whitepaper in English). We believe that the framework can only be developed to its fullest potential in a collaboration with experts from multiple disciplines, such as experts from academia, car manufacturers and safety institutes.

Declaration of Competing Interest

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

Data availability

No data was used for the research described in the article.

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References

Abbink, D. A., Carlson, T., Mulder, M., de Winter, J. C., Aminravan, F., Gibo, T. L., & Boer, E. R. (2018). A topology of shared control systems—finding common ground in diversity. *IEEE Transactions on Human-Machine Systems, 48*(5), 509–525.

Abbink, D. A., & Mulder, M. (2010). Motivation for a neuromuscular basis for haptic shared control. *IFAC Proceedings Volumes, 43*(13), 299–303.

Alshehri, A., Miller, T., & Sonenberg, L. (2019). Improving Performance of Multiagent Cooperation Using Epistemic Planning. *arXiv preprint arXiv:1910.02607*.

Banks, V. A., Plant, K. L., & Stanton, N. A. (2018). Driver error or designer error: Using the Perceptual Cycle Model to explore the circumstances surrounding the fatal Tesla crash on 7th May 2016. *Safety Science, 108*, 278–285.

Boink, R., Van Paassen, M. M., Mulder, M., & Abbink, D. A. (2014). Understanding and reducing conflicts between driver and haptic shared control. *IEEE International Conference on Systems*. Man, and Cybernetics (SMC), 1510–1515.

Borowsky, A., Oron-Gilad, T., Chasidim, H., Ahlström, C., Karlsson J.G., Bakker, B., … Christoph, M. (2020). Behavioural Markers for Degraded Human Performance. Deliverable D1.2 of the H2020 project MEDIATOR.

Bredereke, J., & Lankenau, A. (2002). A rigorous view of mode confusion. *International Conference on Computer Safety, Reliability, and Security*, 19–31.

Brooke, J. (1986). SUS: A "quick and dirty" usability scale". In P. W. Jordan, B. Thomas, B. A. Weerdmeester, & A. L. McClelland (Eds.), *Usability Evaluation in Industry*. London: Taylor and Francis.

Cabrall, C. D., Eriksson, A., Dreger, F., Happee, R., & de Winter, J. (2019). How to keep drivers engaged while supervising driving automation? A literature survey and categorisation of six solution areas. *Theoretical Issues in Ergonomics science, 20*(3), 332–365.

Carsten, O., & Martens, M. H. (2019). How can humans understand their automated cars? HMI principles, problems and solutions. *Cognition, Technology & Work, 21*(1), 3–20.

Castelfranchi, C. (1998). Modelling social action for AI agents. *Artificial Intelligence, 103*(1–2), 157–182.

Castritius, S. M., Schubert, P., Dietz, C., Hecht, H., Huestegge, L., Liebherr, M., & Haas, C. T. (2021). Driver Situation Awareness and Perceived Sleepiness during Truck Platoon Driving-Insights from Eye-tracking Data. *International Journal of Human-Computer Interaction*, 1–11.

CFR (2021, September 27). *Equipment, systems and installations*. The Code of Federal Regulations for Aeronautics and Space, Title 14, § 25.1309. https://www.law.cornell.edu/cfr/text/14/25.1309.

Chang, C.-C., Boyle, L. N., Lee, J. D., & Jenness, J. (2017). Using tactile detection response tasks to assess in-vehicle voice control interactions. *Transportation Research Part F: Traffic Psychology and Behaviour, 51*, 38–46.

Cleij, D., Bakker, B., Borowsky, A., Christoph, M., Fiorentino, A., van Grondelle, E., & van Nes, N. (2021). Mediator System and Functional Requirements, Deliverable D1.4 of the H2020 project MEDIATOR.

Crundall, D. (2016). Hazard prediction discriminates between novice and experienced drivers. *Accident Analysis & Prevention, 86*, 47–58.

de Winter, J. C., Eisma, Y. B., Cabrall, C. D. D., Hancock, P. A., & Stanton, N. A. (2019). Situation awareness based on eye movements in relation to the task environment. *Cognition, Technology & Work, 21*(1), 99–111.

Dong, Y., Hu, Z., Uchimura, K., & Murayama, N. (2011). Driver inattention monitoring system for intelligent vehicles: A review. *IEEE transactions on intelligent transportation systems, 12*(2), 596–614.

Doshi, A., & Trivedi, M. M. (2012). Head and eye gaze dynamics during visual attention shifts in complex environments. *Journal of Vision, 12(2):9*, 1–16.

Endsley, M. R. (1995). Toward a theory of situation awareness in dynamic systems. *Human Factors, 37*(1), 32–64.

Endsley, M. R. (2018). Situation awareness in future autonomous vehicles: Beware of the unexpected. *Congress of the International Ergonomics Association*, 303–309.

Endsley, M. R. (2006). Situation awareness. *Handbook of Human Factors and Ergonomics, 3*, 528–542.

EuroNCAP. (2018). Automated Driving Tests accessed July 29, 2021 https://www.euroncap.com/en/vehicle-safety/safety-campaigns/2018-automated-driving-tests/ .

Feigh, K. M. (2011). Incorporating multiple patterns of activity into the design of cognitive work support systems. *Cognition, Technology & Work, 13*(4), 259–279.

Flemisch, F., Abbink, D. A., Itoh, M., Pacaux-Lemoine, M. P., & Weßel, G. (2019). Joining the blunt and the pointy end of the spear: Towards a common framework of joint action, human–machine cooperation, cooperative guidance and control, shared, traded and supervisory control. *Cognition, Technology & Work, 21*(4), 555–568.

Flemisch, F., Heesen, M., Hesse, T., Kelsch, J., Schieben, A., & Beller, J. (2012). Towards a dynamic balance between humans and automation: Authority, ability, responsibility and control in shared and cooperative control situations. *Cognition, Technology & Work, 14*(1), 3–18.

Flemisch, F., Schieben, A., Kelsch, J., & Löper, C. (2008). Automation spectrum, inner/outer compatibility and other potentially useful human factors concepts for assistance and automation. Human Factors for assistance and automation.

Forster, Y., Hergeth, S., Naujoks, F., Krems, J. F., & Keinath, A. (2019a). Empirical validation of a checklist for heuristic evaluation of automated vehicle HMIs. *International Conference on Applied Human Factors and Ergonomics*, 3–14.

Forster, Y., Hergeth, S., Naujoks, F., Krems, J., & Keinath, A. (2019b). User education in automated driving: Owner's manual and interactive tutorial support mental model formation and human-automation interaction. *Information, 10*(4), 143.

Guo, F., Klauer, S.-G., Hankey, J.-M., & Dingus, T.-A. (2010). Near crashes as crashsurrogate for naturalistic driving studies. *Transportation Research Record, 2147*(1), 66–74.

Haberland, H. (1999). The natural and the artificial in language and technology. In *Humane Interfaces: Questions of Method and Practice in Cognitive Technology* (pp. 81–87). Pergamon Press.

Harbers, M., Riemsdijk, M. V., & Jonker, C. M. (2012). Measuring sharedness of mental models and its relation to team performance. *14th International Workshop on Coordination, Organisations, Institutions and Norms*, 106-120.

Hart, S.-G., & Staveland, L.-E. (1988). Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In P.-A. Hancock, & N. Meshkati (Eds.), *Advances in Psychology. Human Mental Workload* (pp. 139–183).

Hergeth, S., Lorenz, L., Vilimek, R., & Krems, J. F. (2016). Keep your scanners peeled: Gaze behavior as a measure of automation trust during highly automated driving. *Human Factors, 58*(3), 509–519.

Hirshfield, L., Costa, M., Bandara, D., & Bratt, S. (2015). Measuring situational awareness aptitude using functional near-infrared spectroscopy. *International Conference on Augmented Cognition*, 244–255.

Hoc, J. M. (2000). From human–machine interaction to human–machine cooperation. *Ergonomics, 43*(7), 833–843.

Hoc, J. M., Mars, F., Milleville-Pennel, I., Jolly, É., Netto, M., & Blosseville, J. M. (2006). Human-machine cooperation in car driving for lateral safety: Delegation and mutual control. *Le travail humain, 69*(2), 153–182.

Hollnagel, E. (2017). Contextual Control Model (COCOM) accessed February 2, 2021 https://erikhollnagel.com/onewebmedia/COCOM.pdf.

Hollnagel, E., & Woods, D. D. (1983). Cognitive systems engineering: New wine in new bottles. *International Journal of Man-Machine Studies, 18*(6), 583–600.

Hollnagel, E., & Woods, D. D. (2005). *Joint cognitive systems: Foundations of cognitive systems engineering*. Boca Raton: CRC Press.

Itoh, M., Flemisch, F., & Abbink, D. (2016). A hierarchical framework to analyze shared control conflicts between human and machine. *IFAC-PapersOnLine, 49*(19), 96–101.

Jian, J. Y., Bisantz, A. M., & Drury, C. G. (2000). Foundations for an empirically determined scale of trust in automated systems. *International Fournal of Cognitive Ergonomics, 4*(1), 53–71.

Kästle, J. L., Anvari, B., Krol, J., & Wurdemann, H. A. (2021). Correlation between Situational Awareness and EEG signals. *Neurocomputing, 432*, 70–79.

Kolekar, S., de Winter, J., & Abbink, D. (2020). Which parts of the road guide obstacle avoidance? Quantifying the driver's risk field. *Applied Ergonomics, 89*, 103196.

Kontogiannis, T., & Malakis, S. (2013). Strategies in controlling, coordinating and adapting performance in air traffic control: Modelling 'loss of control'events. *Cognition, technology & work, 15*(2), 153–169.

Kurpiers, C., Biebl, B., Mejia Hernandez, J., & Raisch, F. (2020). Mode Awareness and Automated Driving—What Is It and How Can It Be Measured? *Information, 11*(5), 277.

Kurpiers, C., Lechner, D., & Raisch, F. (2019). The influence of a gaze direction based attention request to maintain mode awareness. *International Technical Conference on the Enhanced Safety of Vehicles*, 10–13.

Lee, J., Rheem, H., Lee, J. D., Szczerba, J. F., & Tsimhoni, O. (2023). Teaming with Your Car: Redefining the Driver-Automation Relationship in Highly Automated Vehicles. *Journal of Cognitive Engineering and Decision Making, 17*(1), 49–74.

Lee, J. D., & See, K. A. (2004). Trust in automation: Designing for appropriate reliance. *Human Factors, 46*(1), 50–80.

Liang, N., Yang, J., Yu, D., Prakah-Asante, K. O., Curry, R., Blommer, M., … Pitts, B. J. (2021). Using eye-tracking to investigate the effects of pre-takeover visual engagement on situation awareness during automated driving. *Accident Analysis & Prevention, 157*, Article 106143.

Lindgren, T., Fors, V., Pink, S., & Osz, K. (2020). Anticipatory experience in everyday autonomous driving. *Personal and Ubiquitous Computing, 24*(6), 747–762.

Louw, T., Madigan, R., Carsten, O., & Merat, N. (2017). Were they in the loop during automated driving? Links between visual attention and crash potential. *Injury Prevention, 23*(4), 281–286.

Lundberg, J., & Johansson, B. J. (2020). A framework for describing interaction between human operators and autonomous, automated, and manual control systems. *Cognition, Technology & Work*, 1–21.

Marcano, M., Tango, F., Sarabia, J., Castellano, A., Pérez, J., Irigoyen, E., & Díaz, S. (2021). From the Concept of Being “the Boss” to the Idea of Being “a Team”: The Adaptive Co-Pilot as the Enabler for a New Cooperative Framework. *Applied Sciences, 11*(15), 6950.

Mars, F., Deroo, M., & Hoc, J. M. (2014). Analysis of human-machine cooperation when driving with different degrees of haptic shared control. *IEEE Transactions on Haptics, 7*(3), 324–333.

McNeese, N. J., Demir, M., Cooke, N. J., & She, M. (2021). Team Situation Awareness and Conflict: A Study of Human-Machine Teaming. *Journal of Cognitive Engineering and Decision Making, 15*(2–3), 83–96.

Merat, N., Jamson, A. H., Lai, F. C., & Carsten, O. (2012). Highly automated driving, secondary task performance, and driver state. *Human Factors, 54*(5), 762–771.

Merat, N., Seppelt, B., Louw, T., Engström, J., Lee, J. D., Johansson, E., … McGehee, D. (2019). The “out-of-the-loop” concept in automated driving: Proposed definition, measures and implications. *Cognition, Technology & Work, 21*(1), 87–98.

Merritt, S. M., Ako-Brew, A., Bryant, W. J., Staley, A., McKenna, M., Leone, A., & Shirase, L. (2019). Automation-induced complacency potential: Development and validation of a new scale. *Frontiers in Psychology, 10*, 225.

Michon, J. A. (1985). A critical view of driver behaviour models: What do we know, what should we do? In . In: Evans, L. & Schwing, R.C., (Ed.), *Human behaviour and traffic safety*. New York: Plenum Press.

Naujoks, F., Hergeth, S., Keinath, A., Wiedemann, K., & Schömig, N. (2019a). Development and Application of an Expert Assessment Method for Evaluating the Usability of SAE Level 3 Ads HMIs. *System, 3*, L2.

Naujoks, F., Wiedemann, K., Schömig, N., Hergeth, S., & Keinath, A. (2019b). Towards guidelines and verification methods for automated vehicle HMIs. *Transportation Research Part F: Traffic Psychology and Behaviour, 60*, 121–136.

Norman, D. A. (1983). Some observations on mental models. *Mental Models, 7*(112), 7–14.

Ohn-Bar, E., Martin, S., Tawari, A., & Trivedi, M. M. (2014). In *Head, eye, and hand patterns for driver activity recognition* (pp. 660–665). IEEE.

Page, E. B., Webb, E. J., Campbell, D. T., Schwartz, R. D., & Sechrest, L. (1966). Unobtrusive measures: Nonreactive research in the social sciences. *American Educational Research Journal, 3*, 317.

Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors, 39*(2), 230–253.

Patten, C. J. D., Kircher, A., Östlund, J., Nilsson, L., & Svenson, O. (2006). Driver experience and cognitive workload in different traffic environments. *Accident Analysis & Prevention, 38*(5), 887–894.

Payre, W., Cestac, J., & Delhomme, P. (2016). Fully Automated Driving: Impact of Trust and Practice on Manual Control Recovery. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 58*(2), 229–241.

Petermeijer, S. M., Abbink, D. A., & de Winter, J. C. (2015). Should drivers be operating within an automation-free bandwidth? Evaluating haptic steering support systems with different levels of authority. *Human Factors, 57*(1), 5–20.

Petermeijer, S. M., Tinga, A. M., de Reus, A. A., Jansen, R. J., & van Waterschoot, B. M. (2021). What makes a good team? – Towards the Assessment of Driver-Vehicle Cooperation. *Automotive User Interfaces*.

Sarter, N. B., & Woods, D. D. (1995). How in the World Did We Ever Get into That Mode? Mode Error and Awareness in Supervisory Control. *Human Factors, 37*(1), 5–19.

Sarter, N. B., Mumaw, R. J., & Wickens, C. D. (2007). Pilots’ monitoring strategies and performance on automated flight decks: An empirical study combining behavioral and eye-tracking data. *Human factors, 49*(3), 347–357.

Schneemann, F., & Diederichs, F. (2019). Action prediction with the Jordan model of human intention: A contribution to cooperative control. *Cognition, Technology & Work, 21*(4), 711–721.

Schömig, N., Metz, B., & Krüger, H. P. (2011). Anticipatory and control processes in the interaction with secondary tasks while driving. *Transportation Research Part F: Traffic Psychology and Behaviour, 14*(6), 525–538.

Sebanz, N., Bekkering, H., & Knoblich, G. (2006). Joint action: Bodies and minds moving together. *Trends in Cognitive Sciences, 10*(2), 70–76.

Society of Automotive Engineers International J3016 (2018). *Taxonomy and definitions for terms related to on-road motor vehicle automated driving systems.* Warrendale, PA: SAE International.

Stahl, P., Donmez, B., & Jamieson, G. A. (2019). Eye glances towards conflict-relevant cues: The roles of anticipatory competence and driver experience. *Accident Analysis & Prevention, 132*, Article 105255.

Stanton, N. A., Salmon, P. M., Walker, G. H., & Stanton, M. (2019). Models and methods for collision analysis: A comparison study *based on the Uber collision with a pedestrian. Safety Science, 120*, 117–128.

Stapel, J., El Hassnaoui, M., & Happee, R. (2020). Measuring driver perception: Combining eye-tracking and automated road scene perception. *Human Factors.*

Tinga, A. M., Cleij, D., Jansen, R. J., van der Kint, S., & van Nes, N. (2022a). Human machine interface design for continuous support of supervision and self-regulation during automated driving. *Transportation Research - Part F: Traffic Psychology and Behavior, 87*, 102–119.

Tinga, A. M., de Back, T. T., & Louwerse, M. M. (2020). Non-invasive neurophysiology in learning and training: Mechanisms and a SWOT analysis. *Frontiers in Neuroscience, 14*, 589.

Tinga, A. M., Petermeijer, S. M., Abbink, D., & de Reus, A. A. (2022b). Vervolg Kwaliteit Gedeelde Rijtaak: Meerjarenplan [Evaluatie van bestuurder-voertuig Roadmap]. *Rijkswaterstaat.* https://open.rws.nl/open-overheid/onderzoeksrapporten/@164232/vervolg-kwaliteit-gedeelde-rijtaak.

Trivedi, M. M., & Cheng, S. Y. (2007). Holistic sensing and active displays for intelligent driver support systems. *Computer, 40*(5), 60–68.

UNECE. (2020). *Proposal for a New UN Regulation on Uniform Provisions Concerning the Approval of Vehicles with Regards to Automated Lane Keeping System*. 1958 Agreement.

Van der Laan, J. D., Heino, A., & De Waard, D. (1997). A simple procedure for the assessment of acceptance of advanced transport telematics. *Transportation Research - Part C: Emerging Technologies, 5*, 1–10.

Victor, T. W., Tivesten, E., Gustavsson, P., Johansson, J., Sangberg, F., & Ljung Aust, M. (2018). Automation Expectation Mismatch: Incorrect Prediction Despite Eyes on Threat and Hands on Wheel. *Human Factors, 60*(8), 1095–1116.

Vlakveld, W., van Nes, N., de Bruin, J., Vissers, L., & van der Kroft, M. (2018). Situation awareness increases when drivers have more time to take over the wheel in a Level 3 automated car: A simulator study. *Transportation Research Part F: Traffic Psychology and Behaviour, 58*, 917–929.

Woods, D. D., & Hollnagel, E. (2006). *Joint Cognitive Systems: Patterns in Cognitive Systems Engineering.* Boca Raton, FL: CRC Press.

Wickens, C. D., Lee, J., Liu, Y., & Gordon-Becker, S. (2003). *Introduction to Human Factors Engineering* (2nd edition). USA: Pearson.

Zhou, F., Yang, X. J., & de Winter, J. C. (2021). Using Eye-tracking Data to Predict Situation Awareness in Real Time during Takeover Transitions in Conditionally Automated Driving. *IEEE Transactions on Intelligent Transportation Systems*.