HF Topic: Surface Transportation

Towards computational simulations of behavior during automated driving take-overs: A review of the empirical and modeling literatures

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Précis: This study provides a review of automated vehicle take-overs and driver modeling. Time budget, presence and modality of a take-over request, driving environment, secondary task and driver factors significantly influence take-over performance. Evidence accumulation models may adequately capture these effects.

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Abstract

Objective: This article provides a review of empirical studies of automated vehicle take-overs and driver modeling to identify influential factors and their impacts on take-over performance and suggest driver models that can capture them.

Background: Significant safety issues remain in automated-to-manual transitions of vehicle control. Developing models and computer simulations of automated vehicle control transitions may help designers mitigate these issues, but only if accurate models are used. Selecting accurate models requires estimating the impact of factors that influence take-overs.

Method: Articles describing automated vehicle take-overs or driver modeling research were identified through a systematic approach. Inclusion criteria were used to identify relevant studies and models of braking, steering, and the complete take-over process for further review.

Results: The reviewed studies on automated vehicle take-overs identified several factors that significantly influence take-over time and post-take-over control. Drivers were found to respond similarly between manual emergencies and automated take-overs albeit with a delay. The findings suggest that existing braking and steering models for manual driving may be applicable to modeling automated vehicle take-overs.

Conclusion: Time budget, repeated exposure to take-overs, silent failures and handheld secondary tasks significantly influence take-over time. These factors in addition to take-over request modality, driving environment, non-handheld secondary tasks, level of automation, trust, fatigue, and alcohol significantly impact post-take-over control. Models that capture these effects through evidence accumulation were identified as promising directions for future work.

Application: Stakeholders interested in driver behavior during automated vehicle take-overs may use this article to identify starting points for their work.

Keywords: Autonomous driving, Driver behavior, Simulation, Meta-analysis, Control theory

Introduction

Driving crashes are a leading cause of preventable deaths and injuries worldwide (World Health Organization, 2015). In the United States alone, over 35,000 people were killed in car crashes in 2016 (National Center for Statistics and Analysis, 2017). In an effort to reduce these crashes, stakeholders have made significant advances in-vehicle safety technology and automated vehicles. Safety technologies such as forward collision warnings, autonomous emergency braking (AEB), and blind spot monitoring detection systems have had a significant impact on driving safety (Cicchino, 2017, 2018; Fildes et al., 2015). Forward collision warnings and autonomous emergency braking have been associated with a 27 % (Cicchino, 2017) and between 38 % and 43 % (Cicchino, 2017; Fildes et al., 2015) reduction in crashes, respectively. A combination of these technologies has an even greater effect, reducing front-to-rear crashes by approximately 50 % (Cicchino, 2017). Autonomous vehicles promise to accelerate these trends, but they also introduce complex legal and scientific issues. The scientific aspects include the development of infrastructure, mechanical systems, software systems, and interfaces that support automated driving and the relationship between human drivers and the automated system (J. D. Lee, 2018; Merat & Lee, 2012).

The scope of automated vehicle technology can be characterized by the Society of Automotive Engineers (SAE) levels of vehicle automation framework (SAE International, 2018). Each level of the framework assigns responsibilities for vehicle control (i.e. steering, acceleration, and braking), monitoring of the driving environment, and fallback performance between human drivers and the automation. Narrative descriptions of the levels are summarized in Table 1. While technologies at all levels might, in theory, be expected to provide a safety benefit, real-world data are mixed. The Insurance Institute for Highway Safety (IIHS) has performed several on-road analyses to show that current level 1 automation systems have provided a benefit (Cicchino, 2017, 2018). However, initial naturalistic studies, department of motor vehicles databases, and several recent high-profile crashes suggest that issues remain in higher levels of automation (Banks, Eriksson, O'Donoghue, & Stanton, 2018; Banks, Plant, & Stanton, 2017; Banks & Stanton, 2016b; Endsley, 2017; Griggs &

Wakabayashi, 2018; State of California Department of Motor Vehicles, 2018). These safety issues typically center around the interaction between human drivers and vehicle automation. One particular genesis of these issues is the automation take-over process, where drivers must resume control from a vehicle automation often with little or no warning (Banks et al., 2017; Griggs & Wakabayashi, 2018).

Table 1

SAE levels of automation and their descriptions

SAE level of automation	Description
0	No automation present, human driver controls all elements of the driving task and monitors the driving environment
1	Automation controls either the steering or acceleration/braking of the vehicle, while the human controls all other elements of the driving task and monitors the driving environment
2	Automation controls both the steering and acceleration/braking of the vehicle, while the human monitors the driving task and serves as an immediate fallback for the automation, ready to take control with little notice
3	Automation controls both the steering and acceleration/braking of the vehicle and monitors the driving task while the driver serves as a fallback for the automation. Transitions of control are guided by take-over requests except during automation failures.
4	Automation executes all control and monitoring aspects within a specified operational design domain (ODD) and does not require the driver to serve as a fallback for the automation. Human drivers (if any) may assume control after exiting the ODD, but the system does not rely on the driver do so.
5	Automation controls all aspects of the driving task under all roadway and environmental conditions. Input is never expected from a human driver

Note. The grey highlighted rows indicate the area of focus for this review. Adapted from (SAE International, 2018)

Defining automated vehicle take-overs

The automated vehicle take-over process is a transition of control from the automation to a human driver. This transition of control can be viewed as a state transition, initiated by an agent—i.e. the human driver or the automation itself (Z. Lu & de Winter, 2015; Z. Lu, Happee, Cabrall, Kyriakidis, & de Winter, 2016). The transition also represents a resumption of responsibilities including lateral and longitudinal control, monitoring of other road users and the environment, and interacting with the vehicle displays and automated system (Banks & Stanton, 2016a, 2017; Banks, Stanton, & Harvey, 2014). Transitions can be non-emergency or emergency. In a non-emergency take-over scenario, the automation issues a take-over request and the driver responds with a self-paced resumption of manual control (Eriksson & Stanton, 2017b). Emergency take-overs are prompted by a precipitating event (e.g., unexpected lane obstacle) and may or may not be accompanied by a take-over request, depending on whether the automated system detects the need for human intervention (e.g., due to sensor limitations the system may not know that it is not correctly tracking the lane markings). It is generally assumed that in an emergency take-over scenario a driver's ability to resume control safely depends on the extent to which they have remained engaged with monitoring both the automation and external road environment (Banks & Stanton, 2017; Victor et al., 2018), and their physical readiness—i.e. hands on the steering wheel and feet on the pedals (Zeeb, Buchner, & Schrauf, 2015). Thus, the process of resuming control may involve physical, cognitive, and visual (in order to regain situational awareness and assess alternatives) components (SAE International, 2016; Wintersberger, Green, & Riener, 2017; Zeeb et al., 2015). The take-over process is depicted in Figure 1, which is adapted from Zeeb et al. (2015), but extended to include action evaluation and visual scanning. In the figure, the take-over starts at the presentation of some salient, precipitating event (e.g., a take-over request, or a lead vehicle braking), and initiates the physical, visual, and cognitive readiness processes. The physical processes include motor readiness and action execution. The motor readiness process comprises repositioning the hands to the steering wheel and the feet to the pedals, and the action execution phase comprises providing the steering or braking input required to execute the selected evasive action. The visual processes include redirecting gaze to the forward scene then scanning (narrowly or widely) the roadway to gather information to support action selection and evaluation. The cognitive processes include cognitive readiness, action selection, and evaluation. Note that in Figure 1, cognitive readiness and action selection is shown as the maximum latency readiness component, however other situations may require longer motor readiness times than cognitive readiness times. For example, a driver who is eating might decide on an evasive action prior to placing their food in an appropriate location and taking hold of the steering wheel. Following the take-over, drivers enter a perception-action loop where they execute their initial action, evaluate it, and modify behavior if necessary (Markkula, Romano, et al., 2018). While the action execution and evaluation are depicted concurrently in Figure 1, there may be differences in their start times and durations as a driver accumulates feedback on the effectiveness of their chosen evasive actions (Markkula, Romano, et al., 2018; Markkula, Boer, Romano, & Merat, 2018).

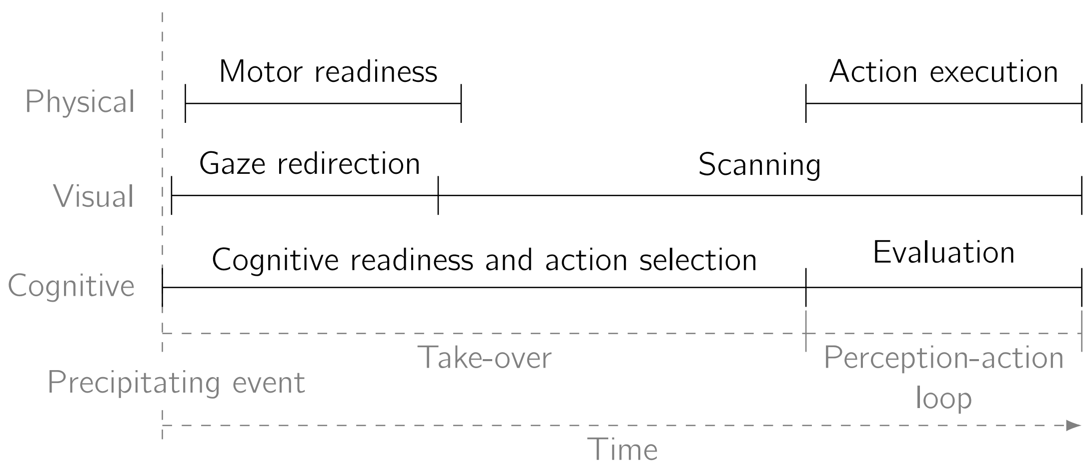

Figure 1. A conceptual model of the physical, visual, and cognitive components of the take-over process (adapted from Zeeb et al., 2015). Note the durations of motor readiness, gaze redirection, and cognitive readiness and action selection represent one possible scenario, in practice, any readiness component could have maximum latency.

The safety of the take-over process is governed primarily by two constraints: the time between the event onset and an impending crash—the take-over time budget—and the effectiveness of the action. If the driver completes the motor and cognitive readiness processes, decides on an action, and effectively executes it within the time-budget, a crash will be avoided. Thus, it is critical to understand factors that influence the time required for motor readiness, gaze redirection, and cognitive readiness as well as factors that influence the quality of action selection and execution. Many of these factors may be similar to those that affect performance in manual driving. For example, a sober driver will likely execute a safer take-over than an alcohol-impaired driver (K. Wiedemann et al., 2018). However, other factors differ between manual and automated driving. The driving environments around automated take-overs may be more constrained, as recent crashes suggest that many take-over requests will, at least with current on-market systems, occur as a result of an impending forward collision (Banks et al., 2017; Griggs & Wakabayashi, 2018). These situations may become more common with the growth of platooning technology, which allows multiple automated vehicles to follow one another at a close distance (Bevly et al., 2017; X.-Y. Lu & Shladover, 2017). Another difference compared to manual driving is an increased interaction with non-driving—or secondary—tasks (Carsten, Lai, Barnard, Jamson, & Merat, 2012; Wandtner, Schömig, & Schmidt, 2018b). Thus, it is reasonable to expect drivers in highly automated vehicles to be engaged with a secondary task prior to a take-over and, by extension, that they may be *out-of-the-loop* (Endsley & Kiris, 1995; Seppelt & Victor, 2016) with the requirements of the driving task. The development of safe automated vehicle technology depends on a thorough understanding of the scope and impact of these factors. The first goal of this review is to investigate the limited but expanding literature on empirical studies of automated vehicles to identify the factors that influence both take-over time and action quality.

Simulation models for driving safety analysis

Understanding factors that influence take-over time and action quality is a critical first step in designing safer systems; however, additional steps are required to integrate these factors into the design process. One method of integration is through simulation models. Simulation models are quantitative models that capture bounds on human physical and cognitive performance and provide realistic predictions of human behavior. Thus, they allow designers to approximate the safety impact of design choices. Simulation models have been used in a broad range of complex systems to improve safety (Pritchett, 2013). The transportation domain has a long history of using simulation models to predict safety impacts of designs (e.g., Perel, 1982). More recently, simulation efforts have been used to assess the safety impacts of advanced driving assistance systems (Bärgman, Boda, & Dozza, 2017; Carter & Burgett, 2009; Gordon et al., 2010; Kusano, Gabler, & Gorman, 2014; Markkula, 2015;

Page et al., 2015; Roesener, Hiller, Weber, & Eckstein, 2017; Van Auken et al., 2011). Although they differ in their specific methodologies, these assessments follow a process of integrating data and simulation models to predict safety outcomes. Figure 2 illustrates how driver models, pre-crash kinematic driving data (from driving simulation or naturalistic studies), and driving assistance systems or automated vehicle algorithms are integrated to produce safety related predictions. Pre-crash kinematic driving data (e.g., speed, acceleration, lead-vehicle headway) are used to specify the driving scenario immediately prior to the driver's corrective action. The driver model and algorithms are used to simulate driver and automated technology behavior leading up to the crash. The outcome can be measured as a percent change in crashes attributable to the driver or driver and automation collaboration compared to manual driving. In this framework, multiple candidate algorithms can be quickly assessed by iterating through this process while keeping the data and model constant. The driver model is a significant component of this process, as poor model selection may undermine the accuracy of the safety related predictions (Bärgman et al., 2017; Roesener et al., 2017). When well suited models are used, this simulation method can produce accurate and precise results. For example, Roesener et al. (2017) found their Hidden Markov Model-based simulation approach predicted actual crash occurrence within 3.5 %. As mentioned, so far this type of methodology has been applied mainly to advanced driving assistance systems, but its importance in the context of automation seems even greater, since conclusive proof of safety of an automated system under development will be very difficult to obtain from real world testing alone (Kalra & Paddock, 2016). Assuming that all the needed models are in place, computational simulations can allow faster than real-time testing of huge numbers of potential take-over scenarios, for example, to help identify situations where risks are high and system modifications may be needed. Thus, the second goal of this review is to examine the literature on driver modeling to identify models that are best suited for take-over scenarios.

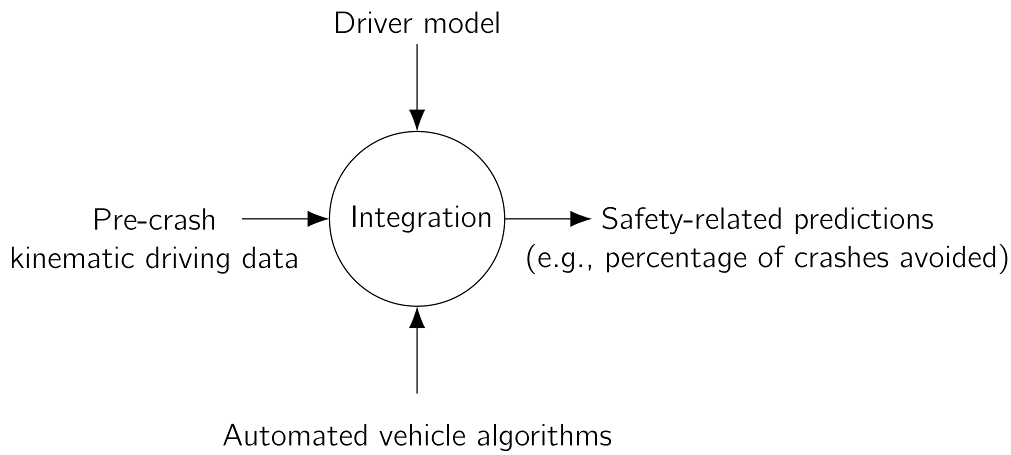

Figure 2. An example process for using driver models to improve safety, adapted from Bärgman et al. (2017).

Identifying influential factors and driver models for take-overs

The previous sections illustrate that automated vehicles present a significant opportunity to improve driving safety, that a limit of this opportunity is in the automation take-over process, and that driver models of the take-over process are an integral tool for improving designs and assessing the impact of autonomous vehicles. Two main challenges in using driver models for improving take-over safety are: (i) identifying and estimating the impact of factors that influence take-overs and post-take-over control, and (ii) identifying driver models that accurately capture these phenomena, to predict driver behavior in the take-over process. The goal of this article is to address these challenges through a review of the current literature on empirical studies of automated vehicle take-overs and quantitative driver modeling. Our focus on factor identification in post-take-over control and modeling differentiates this review from prior reviews and meta-analyses that have focused on identifying significant factors that influence take-over time (de Winter, Happee, Martens, & Stanton, 2014; Eriksson & Stanton, 2017b; Z. Lu et al., 2016; Zhang, de Winter, Varotto, & Happee, 2018) and take-over quality (Gold, Happee, & Bengler, 2017; Happee, Gold, Radlmayr, Hergeth, & Bengler, 2017). Specifically, we examine the empirical work on automated vehicle take-overs to identify a set of factors that influence take-over performance, highlight driver models that capture these factors, and review existing models of automated vehicle take-overs. We close the review with a series of recommendations for future empirical studies and modeling efforts to inform model selection and development.

METHODS

The articles included in this review were identified through a systematic approach of database searches, analysis of reference lists within included articles, and prior knowledge of the authors and their colleagues. The searches spanned five databases: Transportation Research International Documentation (TRID) database, Compendex, Scopus, Web of Science and Google Scholar. Separate searches were conducted for the automated vehicle and driver modeling sections, examples are shown in Table 2. Initial database searches were guided by librarians at the Texas A&M Transportation Institute and the Texas A&M College of Engineering. Global inclusion criteria for the review included peer-reviewed publications, written in English, and published in 2012 or later. Before this date, research on take-overs is scarce, and there is an earlier review of driver models from this year (Markkula, Benderius, Wolff, & Wahde, 2012). Articles published prior to 2012 and dissertations were included if they were central to understanding included work. The searches returned 3,263 results. One hundred and sixty-eight articles were identified via reference list analysis and prior knowledge of the authors and their colleagues. Following a process of duplicate removal and abstract screening, the search results were reduced to a set of 468 candidate articles. Articles included in the review were selected based on separate inclusion and exclusion criteria for automated vehicle take-overs and driver models as described in the remainder of this section.

Table 2

Example database searches

Search type	Primary search terms	Iterative search terms
Automated vehicle take-overs	Driver Behavior Automated and Autonomous Take Over Takeover	
Modeling	Driver Behavior Model	Automated Autonomous Braking Emergency Reaction Steering Take Over Takeover

The review on automated vehicle take-overs included all articles reporting on automated-to-manual control transitions in SAE level 2, 3, or 4 automation. The articles were required to report on an empirical study; including a description of the study, apparatus, method, manipulations, and take-over performance results. Studies could include naturalistic driving, test track driving, simulator driving, or some combination. Both emergency transitions and non-emergency transitions were included to provide context, however, the primary focus of this article is emergency transitions. Experiments where transitions were preceded by an alert as well as those with silent failures were included. Studies including manual driving baseline scenarios were included if the comparison scenarios met the initial SAE level 2 or higher criteria. Notable exclusions in this review include dissertations and conference papers published in other languages — a subset of these are reviewed in Eriksson and Stanton (2017b) and Zhang et al. (2018). Posters presented at major conferences were included if the original poster was accessible. With these criteria, 83 unique articles on automated driving take-overs were included in this review.

The search for the review of driver models was performed iteratively. All iterations included the terms “driver”, “behavior”, and “model” with any suffix variation provided by the respective database. Each iteration also included one iterative search term as shown in the right column of Table 2. A final search was added in order to replicate the searches by Markkula et al. (2012), to verify the previous search methodology. The iterative and overlapping nature of these searches resulted in a substantial number of duplicate articles, but also resulted in at least one unique article per search. Following the search iterations, duplicate articles were consolidated and the remaining articles were abstract screened for relevance. The inclusion criteria for the review of driver models necessitated that the article develop a new model or enhance a prior model that predicted driver behavior relevant to the phases of automated take-overs (as illustrated in Figure 1), even if the models did not directly target automation take-overs. For example, models of evasive maneuver execution in manual driving were included. Articles that reported on model calibration or minor adjustments to prior models were excluded unless they provided critical insights. With these criteria 60 additional articles on driver modeling were included in the review.

Review of automated vehicle take-overs

The topic of transfers of control between humans and automation has been extensively explored by human factors researchers (Bainbridge, 1983; Dekker & Woods, 2002; Endsley & Kaber, 1999; Endsley & Kiris, 1995; Hancock, 2007; Kaber & Endsley, 2004; Sarter & Woods, 2000). However, transitions of automated vehicle control present several new and complex challenges (Seppelt & Victor, 2016). A significant amount of research has been dedicated to exploring these nuances and identifying factors that influence take-over performance. Factors that have been found to influence take-over performance include the time-to-collision at the start of the control transition (i.e. time-budget), secondary task engagement, the presence and modality of a take-over request, the external driving environment, and driver factors (e.g., alcohol impairment). These factors, their definitions, and example studies are summarized in Table 4. This section reviews these factors and their impacts. The section begins with definitions of take-over time and quality, reviews the factors of Table 3, and consolidates the findings into requirements for driver models.

Table 3

Factors and definitions for key terms associated with automated vehicle take-overs

Measure type	Measure	Definition	Example studies
Independent	Take-over time budget	The time-to-collision (or line crossing) at first presentation of a precipitating event	(Gold, Damböck, Lorenz, & Bengler, 2013)
	Secondary task	A non-driving task performed by the driver at the time of the precipitating event	(Radlmayr, Gold, Lorenz, Farid, & Bengler, 2014; Zeeb, Buchner, & Schrauf, 2016)
	Take-over request modality	The modality (e.g., auditory, visual, vibrotactile) of the take-over request	(Naujoks, Mai, & Neukum, 2014; Petermeijer, Bazilinskyy, Bengler, & de Winter, 2017)
	Presence of take-over request	Whether the take-over was preceded by a request	(Strand, Nilsson, Karlsson, & Nilsson, 2014)
	Driving environment	The weather conditions and road type during a take-over, traffic density in vehicles per kilometer, or the available escape paths for the driver	(Gold, Körber, Lechner, & Bengler, 2016; Radlmayr et al., 2014)
	Level of automation	SAE automation level 0 to level 4	(Madigan, Louw, & Merat, 2018; Radlmayr, Weinbeer, Löber, Farid, & Bengler, 2018)
	Driver factors	Driver specific factors such as fatigue or alcohol impairment	(Vogelpohl, Kühn, Hummel, & Vollrath, 2018; K. Wiedemann et al., 2018)
Dependent	Take-over time	The time between the precipitating event and the first demonstrable steering or pedal input from the driver	(Zhang et al., 2018)
	Take-over quality	The driving performance following the precipitating event	(Louw, Markkula, et al., 2017)

Take-over time

While a variety of temporal measures have been used to assess take-over performance, the take-over time is most often measured as the time between the take-over request, or event presentation for silent failures, and the first evidence of demonstrable braking or steering input. Demonstrable input is typically defined by the first exceedance of control input thresholds. The most common thresholds are 2 degrees for steering and a threshold of 10 % actuation from braking (Gold et al., 2017; Louw, Markkula, et al., 2017; Zeeb et al., 2015). Other temporal measures of take-over performance include the time between the warning (or failure) and the redirection of the driver's gaze (Eriksson, Petermeijer, et al., 2017), repositioning of the hands or feet to the controls (Petermeijer, Bazilinskyy, et al., 2017; Petermeijer, Cieler, & de Winter, 2017; Petermeijer, Doubek, & de Winter, 2017), automation deactivation (Dogan et al., 2017; Vogelpohl, Kühn, Hummel, Gehlert, & Vollrath, 2018), or the initiation of the last evasive action (Louw, Markkula, et al., 2017). Table 4 summarizes these measures and their link to driver behaviors. Many of these measures are situation dependent—for example, a driver may already have her hands on the steering wheel at the time of a take-over request and thus would not have a measurable "hands-on reaction time." From a modeling perspective, these measures present opportunities for model validation. For example, if a model's structure includes an eye glance component, one can partially validate the model based on the predicted time to return a driver's glance to the forward roadway. We discuss these reaction-times and the specific factors that influence them inline in the following sections.

Table 4

Temporal measures of take-overs, related driver actions and references

Automated take-over temporal measure	Driver action following precipitating event	Example Reference
Gaze reaction time	Driver redirects gaze to the forward roadway	(Eriksson, Petermeijer, et al., 2017)

Automated take-over temporal measure	Driver action following precipitating event	Example Reference
Feet-on reaction time	Driver repositions feet to the pedals	(Petermeijer, Bazilinskyy, et al., 2017)
Hands-on reaction time	Driver repositions hands to the steering wheel	(Petermeijer, Bazilinskyy, et al., 2017)
Side mirror gaze time	Driver redirects gaze to the side mirror	(Vogelpohl, Kühn, Hummel, Gehlert, et al., 2018)
Speedometer gaze time	Driver redirects gaze to the instrument panel	(Vogelpohl, Kühn, Hummel, Gehlert, et al., 2018)
Indicator time	Driver activates turn signal (or indicator light)	(S. Li, Blythe, Guo, & Namdeo, 2018)
Automation deactivation time	Driver deactivates the automation by braking/steering action or pressing a button	(Dogan et al., 2017)
Take-over time	Driver depresses brake pedal more than 10% or turns the steering wheel more than 2 degrees	(Zhang et al., 2018)
Action time	Driver initiates the final evasive action	(Louw, Markkula, et al., 2017)

Take-over quality

Take-over quality, or post-take-over control, comprises a broad range of metrics intended to measure the take-over performance. Metrics explored in the literature include mean, minimum and maximum lateral and longitudinal acceleration (or their combined magnitude), time to collision statistics (TTC), inverse TTC, minimum time to lane crossing (TLC), minimum time headway to the lead vehicle, minimum distance headway to the lead vehicle, lane position statistics, frequency of collision occurrence, time to complete an evasive maneuver, steering angle based metrics, maximum derivative of the control input that drivers used to avoid the collision, speed statistics, and lane change error rates. The complete set of metrics used to measure take-over quality in the reviewed studies is shown in Table 5. The diverse definitions of take-over quality make summative analysis difficult and thus there is a significant need for a convergence of measures in future studies. From a modeling perspective, these metrics provide a similar opportunity for validation, but also provide insight into the impact of various factors on lateral (i.e. steering) and longitudinal control. Such impacts can be used to guide model selection for braking (longitudinal) and steering (lateral) control models. In the following sections, we separate the impacts of each factor on lateral and longitudinal control in order to align with this model selection process.

Table 5

Summary of take-over quality metrics used in the reviewed studies

Take-over quality metric	Units	Studies employing the metric
Maximum/Minimum/Mean lateral acceleration	$[m/s^2]$	(Feldhütter, Gold, Schneider, & Bengler, 2017; Gold, Berisha, & Bengler, 2015; Gold, Damböck, Bengler, & Lorenz, 2013; Gold, Damböck, Lorenz, et al., 2013; Gold et al., 2016; Gonçalves, Happee, & Bengler, 2016; Kerschbaum, Lorenz, & Bengler, 2015; Körber, Baseler, & Bengler, 2018; Körber, Gold, Lechner, Bengler, & Koerber, 2016; Kreuzmair, Gold, & Meyer, 2017; Lorenz, Kerschbaum, & Schumann, 2014; Louw, Kountouriotis, Carsten, & Merat, 2015; Louw, Merat, & Jamson, 2015; Wan & Wu, 2018; K. Wiedemann et al., 2018; Zeeb et al., 2016)
Maximum/Minimum/Mean longitudinal acceleration	$[m/s^2]$	(Clark & Feng, 2017; Feldhütter et al., 2017; Gold, Berisha, et al., 2015; Gold, Damböck, Bengler, et al., 2013; Gold, Damböck, Lorenz, et al., 2013; Gold et al., 2016; Gonçalves et al., 2016; Kerschbaum et al., 2015; Körber et al., 2016, 2018; Kreuzmair et al., 2017; Lorenz et al., 2014; Louw, Kountouriotis, et al., 2015; Radlmayr et al., 2014; Wan & Wu, 2018; K. Wiedemann et al., 2018)
Maximum resultant acceleration	$[m/s^2]$	(Gold, Damböck, Bengler, et al., 2013; Hergeth, Lorenz, & Krems, 2017; Kerschbaum et al., 2015; S. Li et al., 2018; Lorenz et al., 2014; Wandtner et al., 2018b)
Brake input rate	Count	(Eriksson, Petermeijer, et al., 2017)

Take-over quality metric	Units	Studies employing the metric
Minimum/Mean/Inverse time to collision (TTC)	[s]	(Bueno et al., 2016; Feldhütter et al., 2017; Gold, Berisha, et al., 2015; Gold et al., 2016; Gonçalves et al., 2016; Hergeth et al., 2017; Körber et al., 2018, 2016; S. Li et al., 2018; Louw, Markkula, et al., 2017; Radlmayr et al., 2014; Strand et al., 2014; Wan & Wu, 2018; Wandtner, Schömig, & Schmidt, 2018a; K. Wiedemann et al., 2018)
Minimum time to lane crossing (TLC)	[s]	(Zeeb, Härtel, Buchner, & Schrauf, 2017)
Minimum time headway to the lead vehicle	[s]	(Schmidt, Dreißig, Stolzmann, & Rötting, 2017; Strand et al., 2014; Zeeb et al., 2017)
Minimum distance headway to the lead vehicle	[m]	(Louw, Kountouriotis, et al., 2015; Schmidt et al., 2017; K. Wiedemann et al., 2018; Zeeb et al., 2017)
Maximum/Mean/Standard deviation of lane position	[m] or [ft]	(Brandenburg & Skottke, 2014; Clark & Feng, 2017; Eriksson & Stanton, 2017a; Merat, Jamson, Lai, Daly, & Carsten, 2014; Mok, Johns, Lee, Ive, et al., 2015; Mok, Johns, Lee, Miller, et al., 2015; Naujoks et al., 2017, 2014; Shen & Neyens, 2014; Vogelpohl, Kühn, Hummel, Gehlert, et al., 2018; Wandtner et al., 2018b; K. Wiedemann et al., 2018; Zeeb et al., 2016, 2017)
Crash rate	Count	(Körber et al., 2016; S. Li et al., 2018; Louw, Kountouriotis, et al., 2015; Radlmayr et al., 2014; van den Beukel & van der Voort, 2013; Wan & Wu, 2018; Wandtner et al., 2018a)
Time to complete a lane change	[s]	(Bueno et al., 2016; Louw, Merat, et al., 2015)
Lane change error rate	Count	(Kerschbaum et al., 2015; Mok, Johns, Lee, Ive, et al., 2015; Mok, Johns, Lee, Miller, et al., 2015; Naujoks et al., 2017; Schmidt et al., 2017; Wandtner et al., 2018b)
Maximum/Standard deviation of steering wheel angle	[rad] or [deg]	(Bueno et al., 2016; Clark & Feng, 2017; Eriksson & Stanton, 2017b, 2017a; S. Li et al., 2018; Shen & Neyens, 2014; K. Wiedemann et al., 2018)
Maximum steering wheel velocity	[rad/s]	(K. Wiedemann et al., 2018)
High frequency steering control input	Count	(Merat et al., 2014)

Take-over quality metric	Units	Studies employing the metric
Minimum/Maximum/Mean/Standard deviation of velocity	[m/s] or [km/h]	(Brandenburg & Skottke, 2014; Bueno et al., 2016; Clark & Feng, 2017; Merat, Jamson, Lai, & Carsten, 2012; Merat et al., 2014; Naujoks et al., 2017; K. Wiedemann et al., 2018)
Maximum derivative of the control input that drivers used to avoid the collision	[deg] or [rad/s]	(Louw, Markkula, et al., 2017)

Take-over time budget

Take-over time budget typically refers to the TTC or TLC at the time of the take-over request, or critical event onset for silent failures. However, there is some variance in the literature on the precise definition, as in some studies, a take-over request is given several seconds before a critical event onset. In these cases, time budget is defined as the sum of time from the take-over request and TTC at the critical event (e.g., Clark & Feng, 2017; Vogelpohl, Kühn, Hummel, Gehlert, et al., 2018). A broad range of take-over time budgets have been explored in the literature (Eriksson, Banks, & Stanton, 2017; Eriksson & Stanton, 2017b; Payre, Cestac, & Delhomme, 2016; Wan & Wu, 2018; Zeeb et al., 2015). The mean time budget in the reviewed papers is approximately 8 s, however, the most common value is 7 s. While nearly all the reviewed studies included a time budget for control transitions, several specifically evaluated the effects of varying time budgets on take-over time and post-take-over control; these two aspects will be reviewed in the two subsections below.

Take-over time budget effect on take-over time

Studies have found that take-over time budgets strongly influence the drivers' take-over time. Generally longer take-over time budgets lead to longer take-over times (Gold, Damböck, Lorenz, et al., 2013; Gold et al., 2017; Payre et al., 2016; Zhang et al., 2018) This effect is particularly strong between emergency (i.e. impending crash) and non-emergency scenarios (Eriksson & Stanton, 2017b; Payre et al., 2016). In a meta-analysis, Gold et al. (2017) attributed a 0.33 s increase in take-over time per a 1 s increase in time budget for time-budgets between 5 and 7.8 s. Figure 3 shows a meta-analysis of the presently reviewed studies extending to a wider range of time budgets from 3 to 30 s. The slope of the obtained regression line suggests a 0.27 s increase in take-over time per a 1 s increase in time budget. Interestingly, these meta-analyses align closely with the findings from manual driving by Markkula and colleagues, who showed a 0.2-0.3 s increase in action time for manual drivers, per 1 s increase in rear-end emergency time budget (Markkula, Engström, Lodin, Bärgman, & Victor, 2016, Fig. 10; average α_B in the 0.2-0.3 range). Zhang et al. (2018) also found this relationship between time budget and take-over time in their meta-analysis, and additionally demonstrated a linear relationship between the mean and standard deviation of take-over times; i.e., multiplying the mean take-over time by some factor also multiplies the variability of take-over times by the same factor. Again, this aligns with the findings on brake reaction times from manual driving (Markkula, Engström, et al., 2016; Eq. (2) and Fig. 10).

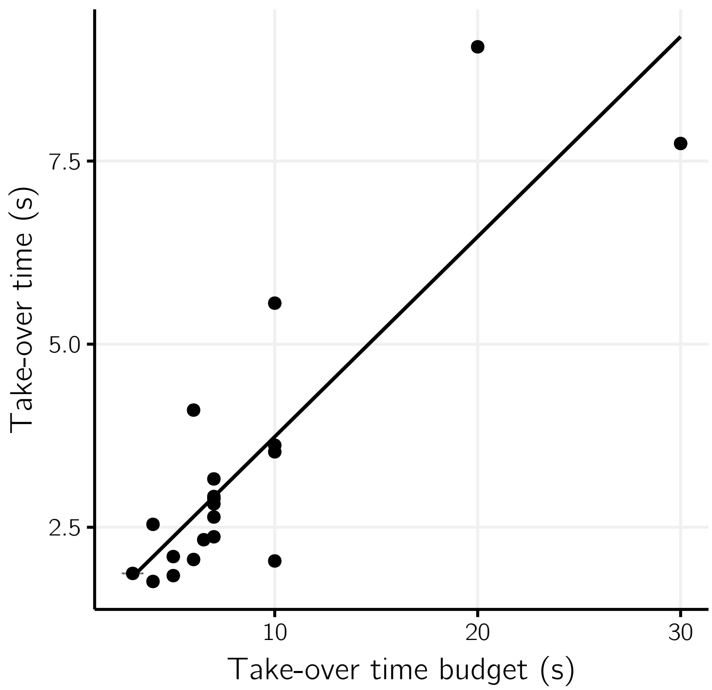

Figure 3. Meta-analysis of mean take-over time by take-over time budget. Take-over time is defined as the time between the take-over request and the driver providing demonstrable responses (i.e. steering or braking greater than a threshold or pressing a button to disengage the automation).

Take-over time budget effect on post-take-over control

Several studies found that shorter take-over time budgets deteriorate post-take-over control. These deteriorations are associated with shorter minimum TTC, greater maximum lateral and longitudinal accelerations (Wan & Wu, 2018), higher crash rates (van den Beukel & van der Voort, 2013; Wan & Wu, 2018), greater standard deviation of lane position, and greater standard deviation of steering wheel angle (Mok, Johns, Lee, Ive, et al., 2015; Mok, Johns, Lee, Miller, et al., 2015). Take-over time budgets also significantly impact the driver's choice of post-take-over response (i.e. braking, steering or a combination), with braking becoming more common at lower time budgets (Gold, Damböck, Lorenz, et al., 2013; Gold et al., 2017). This trend in decision-making is also aligned with manual driving (S. E. Lee, Llaneras, Klauer, & Sudweeks, 2007).

Summary of take-over time budget effects

Take-over time budget refers to the TTC or TLC at the time of the take-over request or onset of the precipitating event or automation failure. The time budget has been shown to significantly increase take-over time with an approximately 0.3 s increase per a 1 s increase in time budget. In addition, the time budget significantly impacts lateral and longitudinal aspects of the post-take-over control as well as choice of maneuver—lower time budgets lead to more braking responses. Collectively these results align with findings from analyses of manual driving, which suggests that models used for manual driving may be translated to automated vehicle take-overs.

Secondary tasks

Secondary tasks are non-driving related activities that drivers perform in addition to monitoring driving automation. A wide range of secondary tasks have been explored in the literature including both artificial and naturalistic tasks. We define artificial tasks as highly controlled and validated interactions (e.g., Surrogate reference task (SuRT) or n-back) and naturalistic tasks as any real-life activity (e.g., reading or interacting with in-vehicle technology), even if it was partially controlled. Table 6 shows a comprehensive summary of secondary tasks explored in the take-over literature. The remainder of this section details the impact of secondary task types on take-over time and post-take-over control consolidated by their modality.

Table 6

Summary of secondary tasks used in the reviewed studies

Type of task	Modality	Secondary task	Description	Related studies
Artificial	Visual, Motoric	Surrogate reference task (SuRT)	Presentation of targets and distractors, targets have to be identified and selected by their columns	(Feldhütter et al., 2017; Gold, Berisha, et al., 2015; Gold, Damböck, Bengler, et al., 2013; Gold, Damböck, Lorenz, et al., 2013; Hergeth et al., 2017; Hergeth, Lorenz, Krems, & Toenert, 2015; Kerschbaum et al., 2015; Körber et al., 2018; Körber, Weißgerber, Blaschke, Farid, & Kalb, 2015; Lorenz et al., 2014; Petermeijer, Bazilinskyy, et al., 2017; Radlmayr et al., 2014)

<table>
<tr><th>Type of task</th><th>Modality</th><th>Secondary task</th><th colspan="2">Description</th><th>Related studies</th></tr>
<tr><td rowspan="7"></td><td>Visual</td><td>Rapid serial visual presentation (RSVP)</td><td colspan="2">Serial presentation of targets and distractors, targets have to be reacted to by pressing a button</td><td>(K. Wiedemann et al., 2018)</td></tr>
<tr><td>Cognitive</td><td>Twenty question task (TQT)</td><td colspan="2">20 yes/no verbal questions</td><td>(Gold, Körber, Hohenberger, Lechner, & Bengler, 2015; Gold et al., 2016; Körber et al., 2016; Merat et al., 2012; Petermeijer, Doubek, et al., 2017)</td></tr>
<tr><td>Cognitive</td><td>n-back</td><td colspan="2">Serial presentation of targets and distractors, target n steps before current stimulus has to be recalled</td><td>(Gold, Berisha, et al., 2015; Louw, Markkula, et al., 2017; Louw, Madigan, Carsten, & Merat, 2017; Radlmayr et al., 2014)</td></tr>
<tr><td>Cognitive, Motoric</td><td>Manual shape identification</td><td colspan="2">Fitting different shapes through the holes in a bag</td><td>(Gold, Berisha, et al., 2015)</td></tr>
<tr><td>Cognitive, Motoric</td><td>Oddball task</td><td colspan="2">Presentation of a series of auditory stimuli and distractors, target stimuli have to be reacted to by pressing a button</td><td>(Körber, Cingel, Zimmermann, & Bengler, 2015)</td></tr>
<tr><td>Visual, Cognitive</td><td>Heads-up display interaction</td><td colspan="2">Projection of a series of web-based IQ test questions on a heads-up display requiring verbal answers</td><td>(Louw, Markkula, et al., 2017; Louw, Madigan, et al., 2017; Louw & Merat, 2017)</td></tr>
<tr><td>Visual, Cognitive, Motoric</td><td>Visual adaptation of the Remote Association Test</td><td colspan="2">Finding the target word that links three presented images among the mixed letters</td><td>(Bueno et al., 2016)</td></tr>
<tr><td rowspan="2">Naturalistic</td><td>Visual, Cognitive, Motoric</td><td rowspan="2">Composing text</td><td rowspan="2">Writing an email, completing a missing word or transcribing a given sentence</td><td>Handheld device</td><td>(Gold, Berisha, et al., 2015; Wan & Wu, 2018; Wandtner et al., 2018a)</td></tr>
<tr><td>Visual, Cognitive, Motoric</td><td>Mounted device</td><td>(Wandtner et al., 2018a, 2018b, Zeeb et al., 2015, 2016)</td></tr>
</table>

Type of task	Modality	Secondary task	Description		Related studies
	Visual, Cognitive, Motoric	Reading text	Reading a magazine, newspaper, article, book or a given sentence	Handheld device	(Dogan et al., 2017; Eriksson & Stanton, 2017a, 2017b; Forster, Naujoks, Neukum, & Huestegge, 2017; Miller et al., 2015; Naujoks et al., 2014; Vogelpohl, Kühn, Hummel, Gehlert, et al., 2018; Wan & Wu, 2018; Wandtner et al., 2018a; Wright et al., 2017b, 2017a; Zeeb et al., 2017)
	Visual, Cognitive			Mounted device	(S. Li et al., 2018; Louw, Merat, et al., 2015; Petermeijer, Doubek, et al., 2017; Wandtner et al., 2018a; Zeeb et al., 2016, 2017)
	Visual, Cognitive, Motoric	Proofreading text	Reading the mistakes of a given sentence aloud	Handheld device	(Zeeb et al., 2017)
	Visual, Cognitive			Mounted device	(Zeeb et al., 2017)
	Visual, Cognitive, Motoric	Watching a video	Watching video stream with or without instruction to answer questions	Handheld device	(Miller et al., 2015; Mok, Johns, Lee, Miller, et al., 2015; Wan & Wu, 2018)
	Visual, Cognitive			Mounted device	(Petermeijer, Doubek, et al., 2017; Walch, Lange, Baumann, & Weber, 2015; Zeeb et al., 2016)
	Visual, Cognitive, Motoric	Playing a game	Playing a game (e.g., quiz game or Tetris)	Handheld device	(Melcher et al., 2015; Vogelpohl, Kühn, Hummel, Gehlert, et al., 2018; Wan & Wu, 2018)
	Visual, Cognitive, Motoric			Mounted device	(Eriksson, Petermeijer, et al., 2017; Schömig, Hargutt, Neukum, Petermann-Stock, & Othersen, 2015; van den Beukel & van der Voort, 2013)
	Visual, Cognitive, Motoric	Device interaction	Internet search or retrieving weather-	Handheld device	(Dogan et al., 2017; Zhang, Wilschut, Willemsen, & Martens, 2017)

Type of task	Modality	Secondary task	Description		Related studies
	Visual, Cognitive, Motoric		related information from an application	Mounted device	(Naujoks et al., 2017; Zeeb et al., 2015)
	Cognitive	Hearing text and repeating	Hearing a sentence and repeating		(Wandtner et al., 2018a)
	Visual, Cognitive	Sleeping	Taking a nap		(Wan & Wu, 2018)
	Visual, Cognitive, Motoric	Free choice of tasks	Free choice by participant (e.g., listening to music)		(Clark & Feng, 2017; Clark, McLaughlin, Williams, & Feng, 2017; Jamson, Merat, Carsten, & Lai, 2013)

Note. Adapted from Naujoks, Befelein, Wiedemann, and Neukum (2016).

Secondary task effect on take-over time

The impact of secondary tasks on take-over time is strongly related to the manual load of the task. Handheld secondary tasks have been shown to increase take-over time (Wan & Wu, 2018; Wandtner et al., 2018a; Zeeb et al., 2017; Zhang et al., 2018). This effect is significant, adding as much as 1.6 s of additional time to the take-over process (Zhang et al., 2018). However, the effect size may depend on the situational urgency and complexity (Zeeb et al., 2017). This additional time is composed of increases in both visual and physical readiness time (Dogan et al., 2017; Vogelpohl, Kühn, Hummel, Gehlert, et al., 2018; Wandtner et al., 2018a; Zeeb et al., 2017; Zhang et al., 2017). One explanation for the impact of handheld devices on take-over time is that switching from a handheld device to the steering wheel after a take-over request requires the driver to initiate a sequence of eye movements to find out where to put down the device and a sequence of hand and arm movements to move the device to a safe storing position (Wandtner et al., 2018a; Zeeb et al., 2017). The effect of non-handheld secondary tasks on take-over time is less clear. Many studies have shown no significant influence of secondary tasks on take-over time (Gold et al., 2017, 2016; Körber et al., 2016; Naujoks et al., 2017; Zeeb et al., 2016) yet others have shown increases in take-over time with different modalities of secondary tasks (Feldhütter et al., 2017; Gold, Berisha, et al., 2015; Ko & Ji, 2018; Radlmayr et al., 2014; Wandtner et al., 2018b; Zeeb et al., 2017; Zhang et al., 2018). These findings may be the result of an interaction effect between complexity in the surrounding environment, requiring time critical and cognitively demanding responses, and secondary tasks (Gold, Berisha, et al., 2015; Radlmayr et al., 2014; Zeeb et al., 2017).

Secondary task effect on post-take-over control

Secondary tasks impact post-take-over control actions (i.e. the decision to steer or brake) and the execution of those actions. The effects are present regardless of task modality. Several studies have found that drivers engaging in a secondary task are biased toward braking actions rather than steering in response to a take-over request (Louw, Merat, et al., 2015; Naujoks et al., 2017). Studies have also found that secondary tasks deteriorate longitudinal post-take-over control resulting more crashes in high traffic situations (Radlmayr et al., 2014) and shorter minimum TTC (Bueno et al., 2016; Gold et al., 2016; Körber et al., 2016; Wan & Wu, 2018) compared to not performing a secondary task. Handheld devices amplify this effect leading to a shorter time headway (Zeeb et al., 2017) and shorter minimum TTC (Wandtner et al., 2018a) compared to mounted devices. Engagement in a secondary task impacts the lateral post-take-over control through an increase in maximum lateral acceleration (Louw, Merat, et al., 2015), average lateral and resultant acceleration, average and standard deviation of lane position (Wandtner et al., 2018b; Zeeb et al., 2016), lane exceedances (Wandtner et al., 2018b), time to change lanes, and maximum steering wheel angle (Bueno et al., 2016) compared to not performing a secondary task. Again, handheld devices amplify this effect compared to mounted devices or non-manual secondary tasks with larger lane deviation and shorter TLC (Zeeb et al., 2017). As with take-over time, these effects may be situationally dependent (Wan & Wu, 2018). A critical remaining question is the extent to which delayed reaction times and action uncertainty influence post-take-over control and the observed effects. The post-take-over control decrements observed with handheld secondary tasks are likely a result of the delayed visual and manual reaction times, which in turn, result in drivers reverting to emergency evasive maneuvers rather than controlled actions (Zeeb et al., 2017). With other types of secondary task, the post-take-over control decrements may be due to brief delays in reaction time (Gold et al., 2016), drivers prolonging the action decision process with compensatory braking (Louw, Merat, et al., 2015), or poor initial action selection (e.g., deciding to execute a lane change when a vehicle is present in the adjacent lane). Driver models may help clarify this confound, through a model fitting and validation process (e.g., Markkula, Romano, et al., 2018; Markkula, Benderius, & Wahde, 2014). In this example, models could be fit to each reaction type and their predictions could be compared to identify the model that most closely reflects observed data.

Summary of secondary task effects

Secondary tasks refer to any non-driving related activity that drivers perform during automated driving. Studies have explored visual, cognitive, and motoric task modalities. Secondary tasks can be performed on a handheld or a mounted device where handheld secondary tasks in particular, significantly increase take-over time. In addition, secondary tasks significantly impact post-take-control and the choice of maneuver. Drivers are more likely to brake if engaged in a secondary task. However, there is a confound between the increases in take-over time and the resulting post-take-over control, wherein the source of post-take-over control decrements is unclear. This confound may be resolved through driver modeling analyses.

Take-over request modality

Take-over request modality refers to the modality of the warning used to notify drivers about a take-over request. Auditory, visual, vibrotactile and a combination of these generic alerts have been explored in previous work. Figure 4 represents the distribution of take-over request modalities observed in the reviewed work. Figure 4 shows that combined visual and auditory feedback is the most common method explored in the literature (Bueno et al., 2016; Dogan et al., 2017; Eriksson, Banks, et al., 2017; Eriksson & Stanton, 2017a, 2017b; Forster et al., 2017; Gold, Berisha, et al., 2015; Gold, Damböck, Bengler, et al., 2013; Gold, Damböck, Lorenz, et al., 2013; Gold, Körber, et al., 2015; Hergeth et al., 2017, 2015; Kerschbaum et al., 2015; Kreuzmair et al., 2017; S. Li et al., 2018; Lorenz et al., 2014; Louw, Markkula, et al., 2017; Louw, Kountouriotis, et al., 2015; Louw, Madigan, et al., 2017; Louw & Merat, 2017; Melcher et al., 2015; Miller et al., 2015; Miller, Sun, & Ju, 2014; Naujoks et al., 2017, 2014; Payre et al., 2016; Radlmayr et al., 2014; Schmidt et al., 2017; Schömig et al., 2015; Vogelpohl, Kühn, Hummel, Gehlert, et al., 2018; Vogelpohl, Kühn, Hummel, & Vollrath, 2018; Walch et al., 2015; Wandtner et al., 2018a, 2018b; K. Wiedemann et al., 2018; Zeeb et al., 2015, 2016, 2017), which is consistent with current vehicles (e.g., Tesla Motors, 2016). The next most frequent modality is an auditory alert (Brandenburg & Skottke, 2014; Clark & Feng, 2017; Clark et al., 2017; Feldhütter et al., 2017; Gold et al., 2016; Gonçalves et al., 2016; Körber et al., 2018, 2016; Körber, Weißgerber, et al., 2015; Louw, Merat, et al., 2015; Merat & Jamson, 2009; Mok, Johns, Lee, Ive, et al., 2015; Mok, Johns, Lee, Miller, et al., 2015; Petermeijer, Bazilinskyy, et al., 2017; Petermeijer, Doubek, et al., 2017; Shen & Neyens, 2014; van den Beukel & van der Voort, 2013; Wright et al., 2017b, 2017a; Wright, Samuel, Borowsky, Zilberstein, & Fisher, 2016). Another area of research on take-over request modalities compares ecological and generic alerts (Figure 5). Ecological alerts, shown in the right side of Figure 5, describe the features of the situation or provide some instruction to the driver. Auditory (Forster et al., 2017; Walch et al., 2015; Wright et al., 2017b, 2017a), visual (Eriksson, Petermeijer, et al., 2017; Lorenz et al., 2014; Walch et al., 2015), and haptic (Melcher et al., 2015) alerts have been explored in this context. Parallel research has also explored real-time communication of automation uncertainty (Beller, Heesen, & Vollrath, 2013).

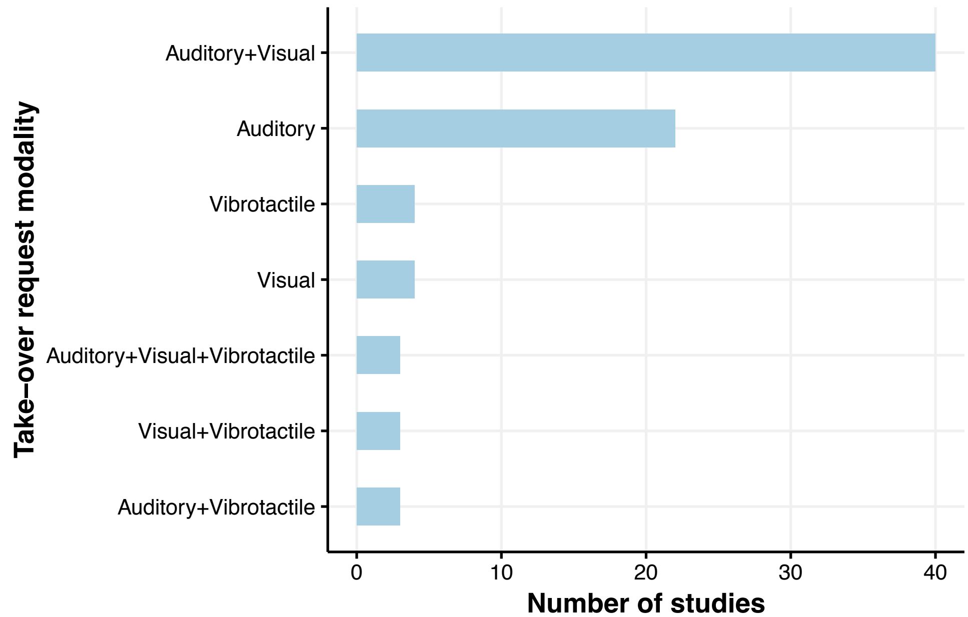

Figure 4. Utilization of take-over request modalities

(a) (b)

Figure 5. Example of a generic visual take-over request, presented on the instrument panel, (a) and an ecological visual take-over request, presented on the forward roadway (b). In (b) the green shape indicates that a lane change is recommended. Photograph from (Lucanos, 2009).

Take-over request modality effect on take-over time

Comparisons between request modalities are rare in the literature, however, some studies have explored these extensively (Naujoks et al., 2014; Petermeijer, Bazilinskyy, et al., 2017; Politis, Brewster, & Pollick, 2015, 2017). Petermeijer, Bazilinskyy, et al. (2017) showed that multimodal cues led to 0.2 s shorter take-over time compared to unimodal cues. Politis et al. (2017) found similar results, adding that visual or vibrotactile unimodal cues led to significantly longer take-over time than multimodal or audio cues. In addition, multimodal take-over requests outperform unimodal in physical readiness time (Naujoks et al., 2014). Regarding the comparison between unimodal take-over requests, Petermeijer, Bazilinskyy, et al. (2017) found a higher visual and physical reaction time for visual take-over requests compared to auditory and vibrotactile. The effect of ecological interfaces is less clear as studies have found both significant (Forster et al., 2017; Politis et al. 2015, 2017) and not significant (Eriksson, Petermeijer, et al., 2017; Lorenz et al., 2014) effects. One explanation for this finding is that poorly timed, verbose, ecological alerts may interfere with the driver's decision-making process and increase take-over time, whereas well-designed and timely ecological alerts may decrease take-over time (Eriksson, Petermeijer, et al., 2017; Naujoks et al., 2017; Walch et al., 2015; Wright et al., 2017a). For example, Walch et al. (2015) observed an increase in take-over time with a visual ecological interface that obscured drivers' vision of the forward roadway for the duration of the take-over time budget. Thus, further clarity is needed on the impacts of well-designed ecological alerts relative to poorly designed alerts.

Take-over request modality effect on post-take-over control

The effect of take-over request modality on post-take-over control, in particular, post-take-over longitudinal control, has not been extensively explored in the literature. Naujoks et al. (2014) observed a higher standard deviation of lane position and maximum lateral position with purely visual requests compared to auditory-visual requests. Ecological alerts have been shown to influence driver braking decisions, generally leading to safer responses (Eriksson, Petermeijer, et al., 2017; Lorenz et al., 2014; Melcher et al., 2015; Wright et al., 2017a). Notably, Petermeijer, Bazilinskyy, et al. (2017) found that directional cues did not result in directional responses from drivers (e.g., vibrotactile alerts on the drivers left-side did not induce left-side lane changes), regardless of take-over request modality. The bias in braking decisions may be due to drivers consciously braking to buy themselves more time for decision making (Eriksson, Petermeijer, et al., 2017; Petermeijer, Bazilinskyy, et al., 2017) or this effect may be caused by the delay in driver's manual reaction times (e.g., Naujoks et al., 2014). The effects on post-take-over control may be an artifact of this decision or the result of the driver's re-acclimation to the driving task. Driver models may help clarify this confound.

Summary of take-over request modality effects

Take-over request modality is the modality of alert that is used to warn the driver about a take-over request. The take-over request could be a generic alert involving auditory feedback, visual feedback, vibrotactile feedback, or a combination. Ecological alerts, which provide a description or an instruction to the driver, have also been explored. Studies have found that multimodal alerts lead to shorter take-over times compared to unimodal alerts. The impact of ecological alerts on take-over time is strongly dependent on conciseness of the alert design. Further research is needed to clarify the impact of ecological alerts and multimodal take-over requests on post-take-over control. Although preliminary findings suggest that multimodal alerts may be a promising future design direction for automated vehicle manufacturers.

Driving environments

Driving environment refers to the traffic situations, road elements, and weather conditions surrounding the automated vehicle during the take-over. Components of driving environment that have been explored in automated driving take-over studies include the traffic density, available escape paths, road types, and weather conditions. While weather conditions (e.g. clear weather, fog, snow, and rain) and road types (e.g., city roads, highways, curved roads, marked and unmarked lanes) have been considered in experimental design, few studies have investigated the impact of these factors on take-over performance directly (S. Li et al., 2018; Louw, Markkula, et al., 2017; Louw, Kountouriotis, et al., 2015). In contrast, the impacts of traffic density and available escape paths on take-over performance have extensively been explored (Eriksson, Petermeijer, et al., 2017; Gold et al., 2017, 2016; Körber et al., 2016; Radlmayr et al., 2014; Zhang et al., 2018).

Traffic density refers to the average number of vehicles occupying a distance of the roadway (e.g., per kilometer, per mile), whereas escape paths refer to paths of travel that the driver can take without being involved in a crash. Traffic density has been explored through several studies as increases or decreases in the number of vehicles per mile (Dogan et al., 2017; Gold et al., 2017, 2016). The range of traffic densities explored in the literature includes 0-30 vehicles per mile. Figure 6 illustrates the escape paths explored in the literature, which include only braking avoidance (a), single-lane lateral avoidance (b), and multiple-lane avoidance (c) (Eriksson, Petermeijer, et al., 2017; Louw, Markkula, et al., 2017; Zeeb et al., 2015). From a modeling perspective, it is important to separate the impacts of these factors as they impact different phases of the take-over process.

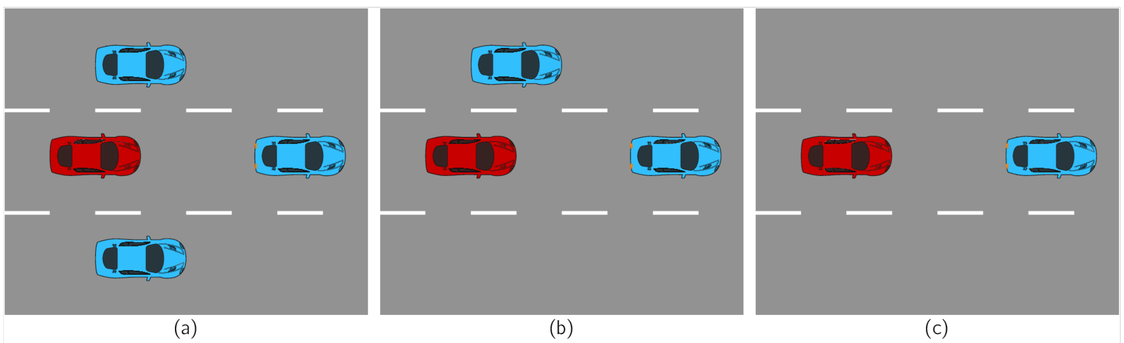

Figure 6. Three escape path scenarios explored in the literature. In each part of the figure, the experimental vehicle is red and the surrounding vehicles are blue. The images show scenarios where drivers may respond with only braking (a), steering to a single lane or braking (b), or steering to any lane and braking (c).

Driving environment effect on take-over time

Both traffic densities and the number of available escape paths have been shown to significantly impact take-over time. Several studies suggest that take-over time increases with increasing traffic density (Gold et al., 2016; Körber et al., 2016; Radlmayr et al., 2014) or when escape paths are reduced (Zhang et al., 2018). However, Gold et al. (2017) found in their meta-analysis that this effect was better described as quadratic centered on 15.7 vehicles/km with lower or higher values leading to decreased take-over time. They hypothesize that 15.7 vehicles/km represents a dilemma zone where it is not clear if changing lanes is a viable alternative, whereas with lower or higher traffic densities drivers may immediately recognize a lane change or braking is the optimal evasive maneuver. Beyond traffic densities and escape paths, at least one study has found that weather conditions and road type impact reaction time. A study by S. Li et al. (2018) found that drivers react significantly faster in the clear weather compared to fog and on city roads compared to the highway.

Driving environment effect on post-take-over control

The dilemma zone hypothesis from Gold et al. (2017) is also supported by findings on post-take-over control. Increasing traffic densities and situations with fewer escape paths bias drivers to responding with braking rather than steering (Eriksson, Petermeijer, et al., 2017; Gold et al., 2017). Higher traffic density is also associated with lower minimum TTC, higher crash rates (Gold et al., 2016; Körber et al., 2016) and higher longitudinal and lateral accelerations (Gold et al., 2016). However, it is unclear if these findings are an artifact of increased use of braking or decision uncertainty (e.g., drivers initially deciding to conduct a lane change, then deciding to abandon the lane change). Adverse weather conditions are associated with decrease in minimum distance headway (Louw, Kountouriotis, et al., 2015), minimum TTC, and increase in resultant acceleration, number of collision or critical encounters, and standard deviation of steering wheel angle (S. Li et al., 2018). Moreover, road type has been shown to significantly impact post-take-over control where city road environments decreased the resultant acceleration compared to highway (S. Li et al., 2018).

Summary of driving environment effects

Traffic situations, road elements, and weather conditions surrounding the take-over are considered as driving environments. Among these environmental factors, traffic density, available escape paths, weather conditions, and road types significantly impact take-over time and post-take-over performance. High traffic density, fewer escape paths, driving in highway environments, and adverse weather conditions delay the take-over time and deteriorate post-take-over control. However, further work is needed to clarify the findings of the studies here, particularly those on weather conditions and road type. In general, driver models must be robust to the various driving environments where take-overs occur.

Presence of a take-over request

A silent failure is a condition where the automation fails or encounters an operational limit without a preceding alert, e.g., due to sensor limitations that the system cannot itself detect. In such conditions, the system implicitly relies on the driver to perceive the failure and resume control. Few current studies have addressed silent failures directly, especially compared to manual driving, however, some insights can be found in similar work. Merat et al. (2014) investigated two types of control transitions: fixed, where the automation disengaged after 6 min of manual driving, and variable, where the automation was disengaged after the drivers looked away from the road center for 10 s. The latter case is an analog for silent failures during secondary task engagement. Merat et al. (2014) found that this silent failure condition generally resulted in worse post-take-over control compared to the fixed transitions. Notably, they found that drivers took approximately 10-15 s to resume control and approximately 40 s to fully stabilize their control after a silent failure. A second study from Strand et al. (2014) compared driver responses to silent longitudinal control failures in adaptive cruise control and level 2 automation. The results showed that drivers in the level 2 automation condition experienced significantly more point-of-no-return events (an analog for crashes) following a complete automation failure. These findings suggest that drivers in automated driving modes may be more sensitive to silent failures than drivers in partially automated vehicles.

Summary of presence of a take-over request effect

Together these studies suggest that silent failures may elongate take-over time relative to more predictable failures. Recovering lateral control and situational awareness following a silent failure may require 40 s or more. Despite these findings, there is still a need for additional work in this area to inform modeling efforts. Additional studies are needed to compare silent automation failures to requested take-overs and manual driving.

Level of automation

Levels of automation (see Table 1) have been found to have a significant impact on take-over performance. While the impacts of different levels of automation (level 1 to level 4) on take-over time and post-take-over control have not been extensively explored, manual driving emergencies (level 0 of automation) have been used as a baseline in several studies (e.g., Eriksson & Stanton, 2017a; Louw, Merat, et al., 2015). In these manual driving baseline conditions, the take-over consists of a response to a precipitating event (e.g., a lead vehicle braking), often while the driver is performing a secondary task. Take-over time in this case is defined as the time between the presentation of the event and the driver's first response input. Generally, compared to these manual driving emergencies, automated driving has been shown to increase the take-over time (Gold, Damböck, Bengler, et al., 2013; Gold, Damböck, Lorenz, et al., 2013; Happee et al., 2017; Radlmayr et al., 2014, 2018) and decrease post-take-over control as measured by standard deviation of lane position (Dogan et al., 2017; Madigan et al., 2018; Vogelpohl, Kühn, Hummel, Gehlert, et al., 2018), standard deviation of speed (Madigan et al., 2018), standard deviation of steering wheel angle (Eriksson & Stanton, 2017a), crash rate (Louw, Kountouriotis, et al., 2015), maximum lateral acceleration (Louw, Kountouriotis, et al., 2015; Louw, Merat, et al., 2015; Madigan et al., 2018), maximum longitudinal acceleration (Louw, Kountouriotis, et al., 2015; Radlmayr et al., 2018), minimum TTC (Radlmayr et al., 2018), and minimum distance headway (Louw, Kountouriotis, et al., 2015). However, the effect of automation on post-take-over control may be simply a result of the increase in take-over time (Happee et al., 2017). Conflicting results have been exhibited between the higher levels of automation. Some studies have shown that an increase in the level of automation has been associated with increase in take-over time (Neubauer, Matthews, & Saxby, 2014; Shen & Neyens, 2014), increase in maximum lane deviation (Shen & Neyens, 2014), and decrease in min TTC (Strand et al., 2014). In contrast, Madigan et al. (2018) found a *decrease* in indicator response time and *increase* in time headway with higher levels of automation during non-critical transitions of control. While the criticality or performance metrics may explain some of the difference in these findings, another significant source of variance is the levels of automation considered. For example, Madigan et al. (2018) compared SAE level 2 and SAE level 3, whereas Shen and Neyens (2014) compared SAE level 1 and SAE level 2.

Summary of level of automation effect

Most studies have explored level of automation effects through a comparison between automated driving and a manual emergency baseline. In these cases, automation has been shown to significantly increase take-over time and decrease post-take-over performance relative to the manual baseline. Few studies were identified that directly compared levels of automation. These studies have shown conflicting findings. Further research is needed to clarify the specific impact of higher levels of automation (level 1 to level 4) on take-over performance, in particular direct comparisons between each level are needed.

Driver factors

In addition to the primary factors mentioned above, prior work has explored the effects of various driver factors on take-over performance. Driver factors explored in the reviewed studies include repeated exposure to take-overs (Gold et al., 2017; Payre et al., 2016), training (Hergeth et al., 2017), prior real-world automation experience (Zeeb et al., 2016, 2017), trust in automation (Körber et al., 2018; Payre et al., 2016), age (Clark & Feng, 2017; Gold et al., 2017; Körber et al., 2016), fatigue (Feldhütter et al., 2017; Körber, Cingel, et al., 2015; Vogelpohl, Kühn, Hummel, & Vollrath, 2018), and alcohol consumption (K. Wiedemann et al., 2018). The remainder of this section details the impact of these factors on take-over time and post-take-over control.

Repeated exposure, training, and real-world automation experience

Prior experience with automated take-overs has a complex but important contribution to take-over performance (Banks & Stanton, 2015; Seppelt & Victor, 2016). Three different types of experience impact take-over performance: repeated exposure to take-overs during experiments, direct training on the take-over process, and prior real-world experience with automated driving functionality. The reviewed studies focused primarily on repeated exposure effects and training although some studies have included long-term real-world exposure as a co-variate in analyses. In line with findings from emergency situations in manual driving (Aust, Engström, & Viström, 2013; J. D. Lee, McGehee, Brown, & Reyes, 2002), effects of repeated exposure were observed in nearly every reviewed study and showed a substantial impact on take-over time. Zhang et al. (2018) found that take-over time decreases an average of 1.1 s between the first and second take-over event. Gold et al. (2017) found a logarithmic effect of repetition, whereby the amount of improvement declined with each repetition. Zeeb et al. (2016) found that repetitions decreased both visual and physical readiness times. Repeated exposures have also been shown to mediate the effect of other factors such as fatigue (Kreuzmair et al., 2017) or take-over request modality (Forster et al., 2017). Prior real-world experience with automated vehicle technologies such as adaptive cruise control has been shown to affect visual reaction time and mediate the learning effect (Zeeb et al., 2017). Training drivers with explanations of take-over process has a similar mediating effect (Hergeth et al., 2017).

Repeated experimental exposures also have shown significant effects on action decisions and post-take-over control. Drivers tend to brake less often following a repeated exposure (Petermeijer, Bazilinskyy, et al., 2017), although the effect may be kinematics dependent. Repetitions of take-over scenarios also result in a significantly lower likelihood of a crash (Gold et al., 2017; Louw, Markkula, et al., 2017; Wandtner et al., 2018a), higher TTC (Gold et al., 2017; Hergeth et al., 2017), lower maximum resultant acceleration (Hergeth et al., 2017), and lower maximum lateral accelerations (Körber et al., 2016). More specifically Russell et al. (2016) showed that drivers exhibit more closed-loop corrective steering behavior after take-overs than in manual driving, but that this effect dissipates after 10 repetitions. Prior experience with automation and training do not appear to influence post-take-over control significantly, but training has been shown to have an interaction effect with repetitions (Hergeth et al., 2017).

Trust

Prior work has defined trust as “the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertainty and vulnerability” (J. D. Lee & See, 2004, p. 51). In the automated vehicle domain, the “agent” refers to the vehicle automation. Trust in automated vehicles has been measured subjectively and objectively. Subjective measures have included questionnaires (Gold, Körber, et al., 2015; Hergeth et al., 2017, 2015; Körber et al., 2018; Miller et al., 2014; Shen & Neyens, 2014). Objective measures explored include eye-tracking parameters such as gaze duration, gaze frequency, percentage of on-road glances (Körber et al., 2018), and the horizontal gaze deviation (Gold, Körber, et al., 2015; Körber et al., 2018). Few studies have found a strong correlation between subjective and objective measures of trust (Körber et al., 2018). Several studies have investigated the impact of subjectively measured trust on take-over performance (Körber et al., 2018; Payre et al., 2016; Shen & Neyens, 2014). There have been conflicting findings regarding this effect. Some studies have found that increase in subjectively measured trust in the automation leads to an increase in take-over time (Körber et al., 2018; Payre et al., 2016) and a decrease in post-take-over control performance, measured by shorter minimum TTC (Körber et al., 2018), maximum lane deviation (Shen & Neyens, 2014), and higher crash rates (Körber et al., 2018). Conversely, lower crash rates have been found with increase in subjectively measured trust (Gold, Körber, et al., 2015). There are several potential sources of these conflicts, for example, the timing and nature of trust measurements and the corresponding statistical analyses. Another source may be the complex, dynamic nature of trust, in which development or erosion of trust in automation and its effects on behavior depend on the interaction among automation, operator, context, and the interface (J. D. Lee & See, 2004). One potential resolution for this conflict would be to include more comprehensive measures, specifically including factors known to influence trust. Several studies have explored these influential factors on trust in automated vehicles including the impacts of automation unreliability (Beller et al., 2013), training (Hergeth et al., 2017), prior information (Körber et al., 2018), repeated exposure to take-overs (Hergeth et al., 2017, 2015), levels of automation (Miller et al., 2014), cultural background (Hergeth et al., 2015), and age (Gold, Körber, et al., 2015). All of these studies have found significant relationships, with the exception of cultural background (Hergeth et al., 2015).

Age

A broad range of driver ages and experience levels have been examined in studies of take-over performance. There is little consensus on the impact of driver age on take-over time. In a study on two groups of young (18-35 years) and older (62-81 years) drivers, no impact of age on hands-on reaction time or feet-on reaction time has been found (Clark & Feng, 2017; Clark et al., 2017). Körber et al. (2016) found similar results on take-over time among two age groups spanning 19-28 years of age and 60-79 years of age. In contrast, the meta-analysis from Gold et al. (2017), which included the Körber et al. (2016) study, found that age had a significant impact on take-over time centered on 46 years of age (i.e. drivers under 46 would have faster take-over times than the mean). Similar results have been found among two groups of young (20-35 years) and old (60-81 years) age where the older group showed significantly slower reaction time (defined as eyes-on, hands-on, and feet-on time), indicator time, and take-over time compared to younger group (S. Li et al., 2018).

The findings on post-take-over control are similarly inconsistent. Körber et al. (2016) showed that older drivers (60-79 years) engaged in more braking and experienced longer minimum TTC, and fewer collisions compared to younger drivers (19-28 years). Wright et al. (2016) found that experienced middle-age drivers (25-59 years) visually identified more hazards with a smaller time budget than inexperienced younger drivers (18-22 years). Gold et al. (2017) did not find a significant impact of age on crash probability but did show that age had a quadratic effect on the probability of brake application, indicating that drivers between the age of 39 and 59 were more likely to brake than younger drivers (19-39 years) or older drivers (older than 59 years). Clark and Feng (2017) found that older drivers (62-81 years) deviated less from the road centerline and drove at a lower speed compared to younger drivers (18-35 years), although older drivers applied more pressure on the brake pedal . In line with this latter finding, S. Li et al. (2018) showed that older drivers (60-81 years) exhibited shorter minimum TTC, greater resultant acceleration, greater deviation of steering wheel angle, and had more collisions than younger drivers (20-35 years). One limitation of these findings is the lack of consensus of age group and experience definitions, in particular, the younger driving groups across these studies contain a broad range of driving experience which may confound the subsequent statistical analyses.

Driver fatigue and drowsiness

Fatigue is a complex construct consisting of three distinct but interrelated states, physical fatigue, drowsiness, and mental fatigue (Brown, 1994). Physical fatigue is a temporary decrement of strength related to repeated or consistent muscular activation (Brown, 1994). Drowsiness is a subjectively experienced desire to fall asleep that is driven by sleep history, extended hours of wakefulness, and circadian rhythms (May & Baldwin, 2009). Mental fatigue, or task-related fatigue, is a subjective disinclination to continue performing one's current task. It can be further divided into passive task-related fatigue—caused by monotonous conditions requiring few driver interventions—and active task-related fatigue—caused by driving in high workload environments for extended periods (May & Baldwin, 2009). The effects of physical fatigue on automated take-overs have not been extensively explored, however, several studies have investigated the effects of drowsiness and task-related fatigue on take-overs. One persistent observation in these studies is that drivers are more prone to fatigue in automated vehicles compared to manually driving (Gonçalves et al., 2016; Jamson et al., 2013; Körber, Cingel, et al., 2015; Neubauer, Matthews, Langheim, & Saxby, 2012; Vogelpohl, Kühn, Hummel, & Vollrath, 2018). The impacts of drowsiness and task-related fatigue on take-over performance are inconclusive. In a stimulus response study, Greenlee, DeLucia, and Newton (2018) observed lower detection rates and longer reaction times over a 40-minute simulated automated drive. Feldhütter et al. (2017) found similar results for gaze reaction times but no significant increase in take-over time between the 5^{th} and 20^{th} minute of an automated drive. In addition, Kreuzmair and Meyer (2017), Schmidt et al., (2017), and Weinbeer et al., (2017) found no significant increase in hands-on time and take-over time between task-related fatigued and alert drivers. Vogelpohl, Kühn, Hummel, and Vollrath, et al. (2018) found no significant differences in take-over time between task-related fatigued drivers and drowsy drivers. They further noted that both fatigued and drowsy drivers with automation were biased towards choosing to brake rather than steer in response to a take-over request due to a rear-end emergency. Finally, Gonçalves et al. (2016) found that subjectively drowsy drivers had higher maximum post-take-over lateral acceleration although they observed no impacts on longitudinal control, or take-over time. The preliminary findings suggest that driver task-related fatigue and drowsiness are relevant modeling components for steering and braking decisions and visual reaction time, however, findings are inconclusive and significant future work is needed. A substantial remaining challenge is identifying the covariance of secondary tasks and fatigue, as secondary tasks have been shown to mitigate task-related driver fatigue (Jamson et al., 2013; Miller et al., 2015; Neubauer et al., 2014; Schömig et al., 2015). Another significant challenge is identifying the contributions of physical fatigue, task-related fatigue, drowsiness, and their combined effects.

Alcohol

Initial studies have shown that alcohol consumption deteriorates take-over performance (K. Wiedemann et al., 2018). K. Wiedemann et al. (2018) investigated the role of blood alcohol concentration (BAC) on take-over performance and found that higher BAC levels increased take-over and manual reaction time and decreased the quality of post-take-over control, as measured by standard deviation of lateral position and maximum longitudinal acceleration. The effect on longitudinal post-take-over control was particularly strong in scenarios that required the driver respond to the take-over with a lane change.

Summary of driver factors effects

Driver factors that have been examined include repeated exposure to take-over events, training, prior experience with automation, trust in automation, age, task-related fatigue, drowsiness, and alcohol. Of these factors repeated exposures have the strongest impact on take-over time and post-take-over control. Task-related fatigue, drowsiness, and alcohol may influence take-over time and performance, however, significant future work is needed to confirm the findings of preliminary studies. The findings on age and trust are inconclusive. Consistency in measurement techniques and statistical analyses may clarify these findings. Collectively the findings suggest that repeated exposures and driver impairment are the most important factors for initial models of take-over performance.

Interaction effects

Few prior studies have explored the interaction effects between the factors identified in this review. Table 7 summarizes these analyses. Significant interaction effects on take-over time have been observed for age and time budget (Clark & Feng, 2017), repeated exposure and training types (Hergeth et al., 2017), repeated exposure and alert modality (Forster et al., 2017), and training and subjectively measured trust (Payre et al., 2016). The findings on repeated exposures suggest that ecological warnings and descriptive trainings lead to lower take-over times in participants first exposure to a take-over. Clark and Feng (2017) found that older drivers had lower take-over times with longer time budgets than younger drivers. Payre et al. (2016) found that participants who experienced a basic practice session (as compared to one with multiple successful automated overtake scenarios) and reported higher subjective trust had higher take-over times. With respect to post-take-over control, significant interactions have been observed for time budget and secondary task (Wan & Wu, 2018), traffic density and age (Körber et al., 2016), and repeated exposures and training (Hergeth et al., 2017). Specifically, Wan and Wu (2018) found that lower time budgets led to lower minimum TTC when drivers were engaged in tasks that disengaged them from the driving environment (e.g., sleeping, watching a movie, or typing) as compared to tasks such as monitoring the roadway or reading. Körber et al. (2016) observed that younger drivers braked less than older drivers at low traffic densities. While these findings are informative, further work is needed to understand them in more detail. For example, further insight is needed to understand the specific secondary tasks that interact with time budget and driving environments, and how the findings on repeated exposures generalize across more than a single repetition.

Table 7

Summary of the findings in interaction effects for take-over time and post-take-over control

Factor	Interactive factor	Studies	Significant results

Time budget		Secondary task (Naturalistic)	(Wan & Wu, 2018)	Minimum TTC was significantly higher for lower time budgets and tasks where drivers were disengaged from the forward roadway
		Age	(Clark & Feng, 2017)	Older drivers had lower hands-on and feet-on reaction times with longer time budgets (7.5 s)
Secondary task	n-back	Request modality	(Petermeijer, Cieler, et al., 2017)	No significant findings
	TQT	Driving environment (Traffic density)	(Gold et al., 2016; Körber et al., 2016)	No significant findings
		Age	(Körber et al., 2016)	No significant findings
	SuRT	Task-related fatigue	(Feldhütter et al., 2017)	No significant findings
	Naturalistic	Level of automation (Manual vs. highly automated)	(Naujoks et al., 2017)	No significant findings
Driving environment	Traffic density	Repeated exposure	(Körber et al., 2016)	No significant findings
		Age	(Körber et al., 2016)	Younger drivers brake less than older drivers at low traffic densities (0 and 10 vehicles/km)
	Weather condition	Age	(S. Li et al., 2018)	Younger drivers' reaction time increased in poor weather conditions (rain, snow, fog).
		Level of automation (Manual vs. L2)	(Louw, Kountouriotis, et al., 2015)	Difference in maximum longitudinal acceleration between manual and automated vehicle was greater in light fog condition compared to heavy fog.
		Driving Environment (Road type)	(S. Li et al., 2018)	Drivers' reaction time (indicator time) to adverse weather conditions are longer on the highway compared to city road. Drivers' reaction time (eyes-on, hands-on, and feet-on) are shorter in clear weather compared to

			fog in both road types with longer time for highway.
Repeated exposure	Training (No training, descriptive training, practice, or a combination)	(Hergeth et al., 2017)	Participants in the practice and no training groups improved take-over time and minimum TTC more between the first and second exposure.
	Age	(Körber et al., 2016)	No significant findings
	Request modality (Ecological and generic vs. generic alerts)	(Forster et al., 2017)	Drivers who received the generic alert had a larger change in automation deactivation time and hands-on time between the first and second take-over
	Level of automation (Manual vs. L2)	(Madigan et al., 2018)	Maximum lateral acceleration has been reduced with repeated exposure to take-overs for drivers in L2 of automation
Training	Trust (Subjectively measured)	(Payre et al., 2016)	With basic training, higher trust led to significantly longer take-over time
Fatigue (task-related vs. drowsiness)	Level of automation (Manual vs. L3)	(Vogelpohl, Kühn, Hummel, & Vollrath, 2018)	No significant findings

Summary of interaction effects

Few interaction effects have been explored in the literature on automated vehicle take-overs. Of the effects that have been explored, the most established are that drivers who receive training or well-designed ecological alerts typically experience shorter initial take-over times. Thus, the design of the alert system is a critical factor in automated vehicle take-over safety. Beyond this finding, significant additional work is needed to investigate the remaining interactions, most notably interactions between secondary tasks, driving environments, and time budgets. As with secondary tasks, driver models may be a useful tool for simulating such experiments and guiding researchers to study designs that will provide the most informative results.

Requirements on models of driver behavior in take-overs

This review shows that the automation take-over process is likely to be impacted by the take-over time budget, the presence of a take-over request, the driving environment, secondary task engagement, the take-over request modality, the level of automation, and driver factors—such as repeated exposure to take-overs. The specific impacts of these factors are summarized in Table 8. Take-over time budget, repeated exposure effect, presence of a take-over request, and handheld secondary tasks have the strongest impact on take-over time. With decreasing time budgets, less exposure to take-overs, silent failures, and handheld secondary tasks, the increase in take-over time leads drivers to begin their action at a point with more kinematic urgency, thereby resulting in more severe and potentially unsafe maneuvers. The take-over time can be further increased by complex traffic scenarios and secondary tasks that create more difficult response decisions. These impacts may be mitigated by multimodal, informative take-over requests; however, the benefits are subject to the utility of the handover design.

Table 8

The impact of factors on take-over time and post-take-over longitudinal and lateral control

Factor affecting take-over	Levels or direction of change of the factor	Impact on take-over time	Impact on lateral control	Impact on longitudinal control
Time budget	Increasing	Increasing	• Decrease in maximum lateral acceleration • Decrease in standard deviation of lane position • Decrease in standard deviation of steering wheel angle	• Decrease in maximum longitudinal acceleration • Increase in minimum TTC • Decrease in crash rates
Repeated exposure to take-over	Increasing	Decreasing	• Decrease in maximum lateral acceleration	• Increase in minimum TTC • Decrease in crash rates
Presence of take-over request	Present	Decreasing	• Increase in high frequency steering corrections	Insufficient evidence

Factor affecting take-over	Levels or direction of change of the factor	Impact on take-over time	Impact on lateral control	Impact on longitudinal control
Secondary task	Handheld vs. mounted	Increasing	• Increase in maximum deviation of lane position • Decrease in minimum TLC	• Decrease in minimum TTC • Decrease in time headway
Alcohol	Increasing	Increasing	• Increase in standard deviation of lane position	• Increase in longitudinal acceleration
Driving environment	Increase in traffic density, Decrease in escape paths, Adverse weather conditions	Increasing	• Increase in maximum lateral acceleration • Increase in standard deviation of steering wheel angle	• Increase in mean and maximum longitudinal acceleration • Decrease in minimum and mean TTC • Increase in brake application frequency • Increase in crash rates • Decrease in minimum distance headway
Secondary task	Non-handheld	No effect to a minor increase	• Increase in maximum and average lateral acceleration • Increase in average deviation of lane position • Increase in maximum steering wheel angle • Increase in time to change lane • Increase in lane change error rates	• Decrease in minimum TTC • Increase in crash rates
Take-over request Modality	Multimodal	Decreasing	• Decrease in standard deviation of lane position • Decrease in maximum lateral position	Insufficient evidence
Level of automation	Increasing	Insufficient evidence	Insufficient evidence	Insufficient evidence
Trust	Increasing	Increasing	Insufficient evidence	Insufficient evidence
Fatigue	Increasing	Insufficient evidence	• Increase in maximum lateral acceleration	Insufficient evidence
Age	Increasing	Insufficient evidence	Insufficient evidence	Insufficient evidence

Note. TTC stands for time to collision and TLC stands for time to lane crossing

Based on these findings, and considering the intended applied context in computational testing outlined in the introduction, we propose the following tentative list of requirements for driver models of the take-over process:

1. Models of automated vehicle take-over should produce similar decisions to manual driving emergencies, namely that drivers should respond more with steering at higher values of TTC and more braking with lower values of TTC.
2. Models should include a mechanism to induce a delay between manual and automated driving.
3. Models should link the take-over time (i.e. time to initial driver action) to the take-over time-budget such that take-over times increase with time-budgets. Model predictions should also show a relationship between mean and standard deviation of take-over times.
4. Models should include the ability to model silent failure situations, where drivers are more likely to fall into a low time budget scenario and respond based on TTC.
5. Models should reflect the delays in responses caused by uncertainty in the driving environment.
6. Models should capture the impact of handheld secondary tasks on take-over time and the negative influence of secondary tasks on post-take-over control.

These criteria could be viewed as a minimal set, with additional specifications needed for modeling levels of automation, impaired drivers, or improvements designs of the human-automation interface. However, at the same time it may not necessarily be the case that one single model needs to meet all of these requirements. Due to the complexity of the involved processes, it may be sensible to limit the scope of models to the requirements of the specific applied question at hand; e.g., in some applied contexts it might make sense to neglect the possibility of silent failures, whereas such failures may instead be the specific focus of other projects and modeling efforts.

Models of driver behavior in automated vehicle take-overs

Models of driving behavior have a rich history in the human factors and vehicle dynamics literatures (Markkula et al., 2012; Michon, 1985; Plöchl & Edelmann, 2007; Saifuzzaman & Zheng, 2014). The models developed in the literature seek to describe driver acceleration, braking, or decision-making. Often models focus on acceleration/braking or steering in a specific context, for example, car following (Markkula et al., 2012). While most of these models are designed to depict manual driving behavior, the prior section suggests that there is significant overlap between manual emergency avoidance behavior and automated vehicle take-over behavior. By extension, models of manual driving behavior may be useful for modeling automated vehicle take-overs. As illustrated in Figure 1, a take-over consists of a readiness and decision-making process, and an action and evaluation process. The actions available to drivers include braking, steering, or a combination of braking and steering. A complete model of a take-over would therefore, include components to predict driver braking behavior, driver steering behavior, and driver decision-making. Our review indicated that few models exist that address all of these behaviors, therefore we discuss them individually.

Within the literature on models of braking, steering, and decision-making, there are different classes of models. In this section, we distinguish between three classes of models, *qualitative*, *statistical* and *process* following the characterization in Markkula (2015). *Qualitative* models describe behavior in a general form without quantifying specific factors. *Statistical* models describe observed behavior quantitatively. *Process* models can both describe and predict driver behavior through mechanisms based on theories of driver control, at some level of granularity. In a more practical sense, *qualitative* and *statistical* models generally do not provide a complete enough account of behavior to allow computational simulation and detailed safety projections, as illustrated in Figure 2, whereas *process* models generally do. These classes are summarized in Table 9 along with a sample of modeling approaches associated with each class that have been applied to driving behavior.

Table 9

Qualitative, Statistical, and Process models reviewed in this analysis paired with examples

Model Class	Modeling approach	Example
Qualitative	State models	(Z. Lu et al., 2016)
	Network models	(Banks & Stanton, 2017)
Statistical	Linear regression (ANOVA)	(Gold et al., 2017)
	Logistic Regression	(Venkatraman, Lee, & Schwarz, 2016)
	Utility (or regret) theory	(Kaplan & Prato, 2012b)

Process	Control theoretic models	(Salvucci & Gray, 2004)
	Cognitive architectures	(Bi, Gan, Shang, & Liu, 2012)
	Kinematics-based models	(Gipps, 1981)
	Evidence accumulation models	(Markkula, 2014)

Our goal in this review is to identify promising *process* models of automated vehicle take-overs. Therefore, we organize this section by *process* models of braking, models of steering, and then follow with a review of *statistical* models of driver decision-making and comprehensive models of automated vehicle take-overs.

Models of driver braking behavior

The empirical work on automated vehicle take-overs suggests that the TTC (or take-over time budget) at the transition of control is one of the principal determinants of take-over time and post-take-over longitudinal control (Gold et al., 2017; Zhang et al., 2018). This finding aligns with prior work on braking in manual driving, which demonstrates that TTC is a primary determinant of the decision to initiate and control braking (D. N. Lee, 1976; Markkula, Engström, et al., 2016). Drivers have direct visual access to an estimate TTC, in the tau parameter—the ratio of the angular size of the forward vehicle and the rate of change of the angular size (D. N. Lee, 1976; D. N. Lee & Reddish, 1981).

The strong link between visual angle and braking behavior observed in empirical analyses is in contrast to the literature on driver braking models, which has predominantly modeled driver braking through relative distance and velocity relationships (Brackstone & McDonald, 1999; Gazis, Herman, & Rothery, 1961; Gipps, 1981; Saifuzzaman & Zheng, 2014). A summary of driver braking models is presented in Table 10. These models have been organized into a taxonomy in Figure 7. The taxonomy illustrates that models can be classified into three types: cellular automata, relative velocity, and visual angle. As discussed previously, empirical evidence suggests that visual angle models are a promising future direction of future work for modeling take-over performance, thus the remainder of this section will focus these models.

Table 10

Summary of car following models

Model name	Conceptual description and intuition	Relevant sources
GHR model	Driver acceleration and braking behaviors are determined by the difference in speed between the focal vehicle and lead vehicle, subject to delays due to reaction times.	(Gazis et al., 1961; Yang & Peng, 2010)
Gipps model	Driver speed is selected to ensure safe stopping distance in the case where the lead vehicle brakes. Speed updates are determined by the desired accelerations and decelerations, vehicle lengths, safety distances, desired speed, estimates of the lead vehicle braking behavior, and are subject to driver reaction times.	(Gipps, 1981; Saifuzzaman, Zheng, Mazharul Haque, & Washington, 2015)
Helly's model	Drivers determine acceleration and braking behavior based on a difference between their desired following distance.	(van Winsum, 1999)
Intelligent Driver Model (IDM)	Driver acceleration and braking behaviors are determined by relationships between desired speeds and spacing and actual speeds and spacing, along with maximum vehicle acceleration.	(Lindorfer, Mecklenbrauker, & Ostermayer, 2017; Ro, Roop, Malik, & Ranjitkar, 2018; Saifuzzaman & Zheng, 2014; Treiber, Kesting, & Helbing, 2006)
Cellular Automata models	Cars move through a matrix cell structure governed by rules. For example, if a vehicle will collide with a preceding vehicle at its current velocity, it will decelerate in the next time step.	(Nagel, Wolf, Wagner, & Simon, 1998)
Perceptual threshold models	Driver accelerations are determined by desired spacing and following distance, subject to perceptual thresholds that limit drivers' perceptions of lead vehicle kinematics.	(Fritzsche & Ag, 1994; R. Wiedemann & Reiter, 1992)
Prospect Theory models	Drivers generate utilities of various accelerations and decelerations based on utility functions and select a braking or acceleration action based on actions with the highest utility.	(Hamdar, Mahmassani, & Treiber, 2015; Hamdar, Treiber, Mahmassani, & Kesting, 2008; Talebpour, Mahmassani, & Hamdar, 2011)
Fuzzy logic models	Driver braking behavior is driven by sets of fuzzy rules that specify driver perception, anticipation, inference, strategy, and action.	(Hao, Ma, & Xu, 2016)

Model name	Conceptual description and intuition	Relevant sources
Affordance Theory	Driver braking behavior is driven by available action affordances and operates as a closed-loop control system.	(Da Lio, Mazzalai, Gurney, & Saroldi, 2018)
Probabilistic response models	Drivers responses are predicted from reaction time and brake force distributions.	(Fitch et al., 2008; Markkula, Engström, et al., 2016; Sivak, Olson, & Farmer, 1982)
Driving by Visual Angle (DVA)	Drivers decide to brake or accelerate based on the difference between the current and desired visual angle (approximated by width and spacing).	(Andersen & Sauer, 2007; D. N. Lee, 1976; Y. Li et al., 2016)
Visual evidence accumulation models	Drivers decide to brake based on sufficient accumulated evidence of the need for braking. Evidence accumulates through errors in expected and observed looming and cues (e.g., brake lights).	(Engström, Markkula, Xue, & Merat, 2018; Markkula et al., 2014; Markkula, Boer, et al., 2018)

Note. Visual angle models are highlighted in gray.

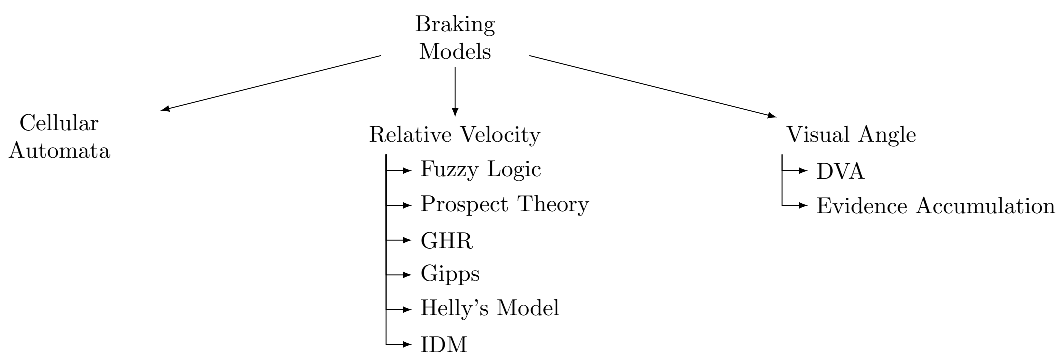

Figure 7. Taxonomy of driver braking models

Visual angle models

Visual angle models originate from the findings of D.N. Lee, who suggested that drivers' responses are driven by tau, which is the ratio of the visual angle to the lead vehicle and its first derivative (D. N. Lee, 1976). The visual angle is defined as the angle of the lead vehicle subtended onto the driver's retina. D.N. Lee (1976) suggested that drivers specifically modulate their braking behavior based on the time derivative of tau, tau dot, suggesting that drivers seek to maintain a constant tau dot of -0.5. Other models have suggested that drivers seek to match their braking with a desired TTC (Andersen & Sauer, 2007). For example, the Driving by Visual Angle (DVA) model relates acceleration changes to a difference between desired and actual visual angles, which are approximately defined by the ratio of the width of the forward vehicle and the following distance, and the current rate of change of the visual angle (θ; see (1)).

$$\ddot{x}(t) = \alpha \left(\frac{1}{\theta_n(t)} - \frac{1}{\tilde{\theta}_n(t)} \right) + \lambda \dot{\theta}_n \tag{1}$$

In the equation, $\ddot{x}$ is the acceleration at time t, θ_n is the actual visual angle, $\tilde{\theta}_n$ is the desired visual angle, and α and λ are constants. The desired visual angle is a function of the focal vehicle's current speed and the driver's desired headway. While the simplest form of the model does not account for multiple driver interactions, individual driver characteristics or reaction-times, several extensions have been developed that accommodate these factors (Jin, Wang, & Yang, 2011; Y. Li et al., 2016). The most significant limitation of these models is the relationship between changes in the visual angle and braking responses. In the most basic specifications, visual angle models lead to a linear relationship between changes in visual angle and braking behavior. This relationship is inconsistent with satisficing behavior that is typically observed in driving (Fajen, 2008; Summala, 2007).

Visual evidence accumulation models

In visual evidence accumulation models, drivers receive evidence for or against the need for a control action and then initiate a response if, and only if, sufficient evidence is available to warrant one (Markkula, 2014; Markkula, Boer, et al., 2018). Evidence in this context can consist of brake light activations in lead vehicles, changes in the visual angle of the lead vehicle (i.e. visual looming), a lane change of the lead vehicle, or any other environmental change that the driver can perceive. Evidence accumulation models may also be viewed through the lens of predictive processing, where drivers use braking to reduce errors between their expectations and observations (Engström, Bärgman, et al., 2018). The evidence accumulation framework has been qualitatively validated for several braking patterns in large naturalistic datasets (Markkula, Engström, et al., 2016; Svärd, Markkula, Engström, Granum, & Bärgman, 2017), and quantitative model fits have been demonstrated for brake response times as observed in simulator studies (Markkula, Lodin, Wells, Theander, & Sandin, 2016; Xue, Markkula, Yan, & Merat, 2018). Importantly, evidence accumulation models capture the phenomena of the kinematics-dependence of take-over time and the variability of response times increasing with average response times, as observed both in manual and automated driving (Markkula, Engström, et al., 2016; Zhang et al., 2018). Evidence accumulation models have been extended to include the effects of cognitive distraction (Engström, Markkula, et al., 2018). In the extended model, cognitive load slows the evidence accumulation process, leading to prolonged reaction times. This approach integrates prior work on Guided Activation Theory, described in (Engström, Markkula, Victor, & Merat, 2017), and aligns with findings from a broad analysis of empirical work on the impact of cognitive load on response times (Engström, 2010).

Key findings and recommendations

The evidence from the empirical review of automated take-overs suggests that there is a strong link between TTC and driver braking responses. Extrapolating similar results from manual driving suggests that drivers may make braking decisions based on visual quantities such as tau, which by extension suggests that models based on such visual quantities may be preferred to relative velocity and cellular automata models. Furthermore, the finding that there is a strong correlation between mean and standard deviation of take-over time (Zhang et al., 2018) suggests that evidence accumulation models should be preferred to simpler stimulus-response visual angle models. Evidence accumulation models can also, in theory, capture the difference between silent and alerted failures, by integrating warning messages as an additional source of evidence for the need of braking.

Models of driver steering behavior

Models of driver steering are typically based on control theory concepts (Jurgensohn, 2007; Markkula et al., 2012; Plöchl & Edelmann, 2007), and they can be classified into three types: closed-loop, open-loop, and hybrid open-closed-loop models. Drivers in closed-loop models are portrayed as active, optimal controllers that seek to minimize angular or positional errors (McRuer, Allen, Weir, & Klein, 1977; Salvucci & Gray, 2004). Drivers in open-loop models periodically provide control input based on a set of learned patterns—sometimes called motor primitives—to correct observed errors (Markkula et al., 2014). Hybrid models combine these concepts—drivers provide initial open-loop input followed by closed-loop corrections (Donges, 1978; Markkula, Boer, et al., 2018). Within these types, models can be further differentiated by the angle(s) or position they attempt to control, the criteria they optimize for, and the inclusion of neuro-muscular dynamics (Markkula et al., 2012). We refer to the latter category as cybernetic models in this review. The accuracy of these models varies significantly based on the driving scenario and surrounding environment that they are applied to (Markkula et al., 2014). Thus, selecting a steering model depends on the scenario and observed behavior.

The empirical review presented earlier suggests that drivers respond with steering primarily in cases where they have a sufficient time budget, however steering may also be used as a last resort to avoid a crash, or when exiting the current lane is the only escape path (Gold et al., 2017; Happee et al., 2017; Zeeb et al., 2017). The patterns of steering observed vary with these scenarios and include both avoidance and corrective actions (Eriksson & Stanton, 2017a; Merat et al., 2014; Russell et al., 2016). Early work in this area suggests that closed-loop models may capture drivers heading and lane position, but they may be insufficient to capture steering behavior (DinparastDjadid et al., 2017). These findings seem to suggest that driver behavior in post-take-over steering may be represented with open-loop or hybrid open-closed-loop controllers. The strong influence of handheld secondary tasks on post-take-over control (Vogelpohl, Kühn, Hummel, Gehlert, et al., 2018; Zhang et al., 2018) also suggests that cybernetic models may be useful in this context. Thus, the remainder of this section will focus on these three types of models.

Open-loop models of driver steering behavior

Open-loop steering models depict driving as an open-loop execution of primitive actions. Primitive actions, in this case, are pre-programmed patterns of control that drivers execute in series. The effect of this change is that drivers tend to execute periodic pulses of behavior rather than sinusoidal waves. Recent work has shown that these models accurately capture driver steering behavior in manual driving (Benderius & Markkula, 2014; Benderius, Markkula, Wolff, & Wahde, 2014; Johns

& Cole, 2015; Markkula et al., 2014). Markkula et al. (2014) compared a series of closed and open loop models for predicting avoidance and stabilization steering in a low friction rear-end emergency scenario. The comparison showed that open-loop avoidance models explained the most variance in steering behavior. Open-loop models were not fit to stabilization steering, where a closed-loop model (Salvucci & Gray, 2004) was found to best fit the experimental data.

Hybrid open-closed-loop models of driver steering

Hybrid open-closed-loop steering models integrate open-loop selection and execution of primitive actions and closed-loop corrective control. The open-loop model components provide anticipatory control and the closed-loop components provide compensatory control to account for unresolved errors (Donges, 1978; Edelmann, Plöchl, Reinalter, & Tieber, 2007). Recently, Martínez-García, Zhang, and Gordon, (2016) developed a hybrid model built on prior work by Gordon and colleagues (Gordon & Srinivasan, 2014; Gordon & Zhang, 2015). The model operates as an act-and-wait controller, meaning that drivers provide periodic corrections when their perceived steering error crosses a threshold. The periodic corrections are based on three primitive functions: ramp, bump, and ripple. The ramp function is a continuous step input, the bump function is a pulse, and the ripple function is sinusoidal. The primitive corrections operate in an open-loop framework, which is followed by a closed-loop compensatory correction. Markkula, Romano, et al. (2018) developed a hybrid model that integrated motor primitives, evidence accumulation, and sensory consequences of motor actions. The model consists of three elements: perceptual processing, control decision and motor output, and the control input to the system. The control system generates control input through a three-phase structure of evidence accumulation, simulation of prediction primitives, and finally a superposition of motor primitives. The effect of this structure is that drivers control a vehicle through accumulating evidence on the need to provide control input, predicting the consequences of actions through simulation, and then executing the patterns of behavior based on perceptual input. In this way, the model is aligned with the evidence accumulation models discussed in the section on braking models.

Cybernetic models of driver steering behavior

Cybernetic models specifically incorporate neuromuscular processing, visual processing, or a combination of the two. Mars and Chevrel (2017) described a cybernetic driver steering model originally proposed and enhanced in (Mars, Saleh, Chevrel, Claveau, & Lafay, 2011; Saleh, Chevrel, Mars, Lafay, & Claveau, 2011; Sentouh, Chevrel, Mars, & Claveau, 2009). The model represents steering as a closed loop system where drivers extract anticipatory and compensatory cues then process that input through a neuromuscular system model, based on Hoult and Cole's (2008) work, that converts visual angles to steering wheel torque. The model also depicts distraction through a combination of input (perceptual) noise, driver model parameter adjustments, or torque application (Ameyoe, Chevrel, Le-Carpentier, Mars, & Illy, 2015). Mars and Chevrel (2017) illustrated that the model was sensitive to sensorimotor distraction, although it could not sufficiently differentiate between cognitive and sensorimotor distraction in the current configuration.

Nash and Cole (2016) developed a similar, but more comprehensive driver steering model, incorporating neuromuscular, visual, and vestibular dynamics into a closed-loop control framework. The model was further specified and applied to non-linear (emergency) conditions in Nash and Cole (2018) based on findings from a review on human sensory dynamics (Nash, Cole, & Bigler, 2016). The core model is rooted in the multi-level anticipation and stabilization concept of Donges (1978), however, the Nash and Cole model joins these phases into a single closed-loop controller. In the model, the vehicle generates signals which are passed to visual and vestibular perceptual elements (modeled as transfer functions), these elements pass processed signals to a linear quadratic regulator controller after a time delay and processing with a Kalman filter, the controller signals are passed through a neuromuscular dynamics element back to the vehicle. At each step of the process, Gaussian noise is passed into the model to depict perceptual errors and influences from the environment. Thus, the model provides optimal control in a noisy environment. While the model has not been extensively validated, Nash and Cole (2016) illustrated that it could predict corrective behavior well for aircraft pilots.

Key findings and recommendations

The literature on automated vehicle take-overs suggests that drivers tend to use steering in response to emergency take-overs with long time budgets (Gold et al., 2017). The pattern of steering avoidance follows an anticipatory and compensatory process where drivers provide a large initial steering input followed by a series of smaller corrective inputs. Handheld secondary tasks may interfere with these actions as drivers abandon the task and relocate their hands to the wheel (Wandtner et al., 2018a). The anticipatory and compensatory process can be captured in the open-loop or hybrid open-closed-loop models discussed in this section. While the cybernetic models discussed here are closed-loop, they may be more simply extended to include the neuro-muscular aspects of the transition from handheld secondary task to driving. Furthermore, the extensions of the Mars and Chevrel (2017) model that capture distraction may be advantageous for capturing the impact of secondary tasks on post-take-over control. The benefits of these types of models suggest that both cybernetic models and hybrid open-closed-loop models are viable candidates for modeling post-take-over steering behavior.

Models of steering and braking decisions

As reviewed earlier in this paper, decisions to steer or brake in response to a take-over are impacted by the take-over time budget, surrounding traffic, secondary task, fatigue, ecological alerts, repeated exposure, and age (Gold et al., 2017). When traffic conditions allow, drivers tend to perform a lane change (i.e. steering avoidance maneuver) with larger time budgets (Gold, Damböck, Bengler, et al., 2013; Zeeb et al., 2017). With shorter time budgets, drivers revert to braking responses but may include emergency steering as a “last resort” to avoid a crash (Zeeb et al., 2017). Thus, evasive maneuver decision-making may be viewed as a cascade of multiple decisions and action execution. This type of action may explain why post-take-over speed and steering behavior vary significantly with avoidance maneuver selection (Happee et al., 2017). These factors highlight the criticality of avoidance maneuver selection accuracy in take-over models. This criticality is not reflected in the volume of avoidance maneuver selection models, which is substantially less than steering or braking models. One exception is the model by Markkula, Romano, et al. (2018) discussed in the section on process models further below. However, most of the avoidance maneuver selection models identified by this review were statistical in nature and by extension may not in themselves be enough to permit computational simulation. That said, the findings of these models provide useful links between models of steering and braking that facilitate the development of complete models of take-overs and therefore are important to discuss. The descriptive models of evasive maneuver decisions can be classified by logistic regression models and machine learning models.

Logistic regression models

Venkatraman et al. (2016) compared several logistic regression models of driver braking and steering responses to a lead vehicle braking scenario with a forward collision warning. They found that a model including the optical angle of the forward vehicle and tau best explained their observed data. Increases in optical angle and tau increased the likelihood of braking and conversely decreases in the optical angle and tau increased steering responses with only mild braking. Wu, Boyle, and Marshall (2017) developed a similar logistic regression model that showed driver age and location were predictive of the choice to steer or brake. In the model, drivers older than 39 years of age from urban coastal areas (Washington D.C. and Seattle, WA) were more likely to provide steering input whereas younger drivers from rural areas (Clemson, SC and Iowa City, IA) were more likely to brake only in response to a forward collision warning. In addition to basic logistic regression models, several approaches have described braking and steering choices with mixed logit models (Kaplan & Prato, 2012b, 2012a). Beyond the findings of the simple logistic models, the Kaplan and Prato (2012a, 2012b) models identified the number of road lanes, the type of roadway (one-way or two-way), the presence of a curve, and the roadway lighting conditions as key factors in driver's avoidance decisions, thus aligning with the literature on automation take-overs in highlighting the importance of the traffic scenario for maneuver decisions.

Machine learning models

Hu et al. (2017) developed a decision tree model to predict driver maneuvers during a cut-in scenario. Their model included kinematic variables, such as the distance and time-to-collision to a leading vehicle in the adjacent lane, driver age, and personality factors including extroversion and neuroticism. While the precise relationships are complex, the model structure suggested that lane changes (i.e. steering rather than braking) are associated with low risk (as defined by distance and time-to-collision) environments involving younger extroverted male drivers with high neuroticism. The model predicted driving simulator data well, suggesting that subsequent modeling approaches should consider both objective kinematic factors and driver personality factors. In prior work, Harb, Yan, Radwan, and Su (2009) used decision trees and random forests to model critical factors in angular, head-on, and rear-end crashes. The model identified visibility of an obstruction, distraction, and physical impairment as significant factors in driver avoidance decision-making.

Key findings and recommendations

The literature on models of driver decision-making is notably lighter than that of the steering and braking models. However, it is unique in its focus on driver personality factors. These factors may be critical to the overall take-over performance given the findings of Zeeb et al. (2015), who found that high risk drivers react more slowly to take-over requests, and Eriksson and Stanton (2017b), who observed a large variance in driver responses. Another notable trait of the models reviewed here is the link between visual parameters and driver decision-making (Venkatraman et al., 2016). This link facilitates a connection between models of decision-making, steering, and braking reviewed earlier that are also driven by looming (e.g., Markkula, 2014; Markkula, Boer, et al., 2018). However, substantial additional work is needed in this area to develop more formal, predictive, models to validate this link.

Process models for take-overs

The prior sections illustrate that commonalities exist across models that may explain driver behaviors across various aspects of take-over. However, there has not been an extensively validated modeling approach that explains behavior across the phases of a take-over. As illustrated in Figure 1, such a model would have to capture the driver's perception of the need for a take-over, and the loop of decisions to steer or brake, action execution, and evaluation. The goal of this section is to review existing process models that could capture these phases and provide guidance on further developmental needs.

Seppelt and Lee (2015) presented a model of driver take-overs from an adaptive cruise control system, originally proposed in (Seppelt, 2009). The model contains two driver behavioral elements, one that depicts the driver's understanding of the automation state, and another that depicts driver responses. The driver's understanding of the system is driven by a state-based model based on the work of Degani and Heymann (Degani & Heymann, 2002; Heymann & Degani, 2007). The state-based model pairs driver understanding of the system state and the actual system state. In this way, the model highlights misalignment between the two values. In cases where the driver understanding and actual state are aligned, drivers will immediately respond to requests to intervene. In cases of silent failure, or other situations where drivers' understanding of the system and the actual system state are misaligned, driver responses will be driven by just-noticeable differences in perceptual parameters such as the TTC or the looming effect.

Markkula, Romano, et al. (2018) developed a model that depicts the take-over process through a series of gates, perceptual decisions, and action decisions. The gates are activated by driver gaze locations and the decisions are noisy evidence accumulators driven, for example, by visual looming of a forward vehicle. The perceptual decisions include: whether the driver is catching up with the forward vehicle, if a prior decision to brake is resolving the conflict, and a safety check on changing lanes. The action decisions include looking at the forward roadway, looking for a lane change possibility, increasing braking, and changing lanes. The former two decisions drive driver gaze behavior and the latter two decisions drive maneuver selection. The model qualitatively replicated the impact of time budget on braking/steering decisions as observed by Gold, Damböck, Lorenz, et al. (2013).

Although these models more closely replicate take-over processes, compared to the braking and steering models reviewed earlier, both models require substantial further development to be capable of replicating the full body of experimental results. The Seppelt and Lee model (2015) captures both alerted and latent failures, links responses to perceptual input, and is simulation ready, but is not specifically designed to capture influences of secondary tasks, repeated exposures, surrounding traffic, or steering behavior. The Markkula, Romano, et al. (2018) model captures the qualitative process of take-overs, links the decisions and reactions to driver perceptions, and is also simulation-ready, but it does not capture the influence of handheld secondary tasks, take-over request modalities, and repeated exposures.

Discussion

This review examined the literature on empirical studies of automated vehicle take-overs and driver modeling. The analysis of automated vehicle take-overs extends prior reviews through the consideration of both take-over time and post-take-over control. The analysis of driver models extends prior reviews of driver models to include novel methods for integrating human factors into driver models (e.g., evidence accumulation and cybernetic models), and through its application of empirical findings on take-overs to model selection. Specific further extensions are discussed in the following sections.

Findings from the review on empirical studies of automated vehicle take-overs

The review identified two performance criteria used to measure automated vehicle take-overs—take-over time and post-take-over control (i.e. take-over quality)—and factors that influence them. Take-over time budget, repeated exposure to take-overs, silent failures and handheld secondary tasks are the most influential factors on take-over time. In addition, post-take-over lateral and longitudinal control are significantly impacted by take-over time budget, secondary task engagement, take-over request modality, driving environment, silent failures, repeated exposures, fatigue, trust in the automation, and alcohol impairment. In general, empirical work demonstrates that after a transition of control, drivers often respond similarly to how they respond in emergency situations in manual driving, albeit with an additional delay. The findings on take-over time confirm those of earlier reviews and meta-analyses (Eriksson & Stanton, 2017b; Gold et al., 2017; Happee et al., 2017; Z. Lu et al., 2016; Zhang et al., 2018), however this review provides additional context, specifically associated with driving environments and driver factors. The findings on post-take-over control extend the prior meta-analyses of Gold et al. (2017) and Happee et al. (2017) to systematically define post-take-over control metrics and identify critical factors that influence post-take-over control including take-over request modality, handheld secondary tasks, silent failures, weather conditions, and driver impairment. While significant progress has been made to understand the factors that influence take-over performance, our review indicated several areas in need of future work.

Research needs in automated vehicle take-overs

Modeling behavior in automated take-overs requires a precise understanding of the mechanisms that produce behavior and precise data on the behavior itself. One open question is relationship between take-over time and post-take-over control, specifically if decrements in post-take-over control are the result of delayed reactions, poor decision-making, poor action execution, or some combination of the three. Furthermore, additional work is needed to clarify the interaction effects between the factors here, as most current meta-analyses have focused on purely additive models. With respect to individual factors, additional work is needed to understand the effects of age, silent failures, ecological interfaces, level of automation (SAE level 1 to level 4), trust, driver's disability or limited mobility, and the presence of passengers. Silent failures are perhaps the most critical of these areas, as they have already been observed in fatal automated vehicle crashes (e.g., Griggs & Wakabayashi, 2018). Trust is another critical factor as current research has explored a limited set of measures and dimensions of trust. Future studies should identify reliable measures and investigate the impact of factors such as individual and cultural differences on trust evolution. The studies discussed in Victor et al. (2018) represent significant progress in these two areas, but more work is needed.

Another source of gaps is the experimental paradigms. As with many other areas of transportation research, there is a need to confirm simulator findings in naturalistic settings. The work of Eriksson, Banks, et al. (2017) represents a sound starting point for this work, but further efforts are needed. A subtler issue in the studies observed here is in the time between take-over events. Generally, the studies presented take-over requests with intervals on the order of minutes, whereas in real-world settings it may be several days or months between interruptions. The time between interruptions may influence driver's ability to become invested in secondary tasks and, in the long-term, their ability to retain take-over skills. Additional dependent measures may be needed to further explain the various dimensions of driver responses. In particular, metrics that disambiguate the impacts of delayed responses and action decision on post-take-over control. Psychophysiological measures such as heart rate, brain activity, or eye closure may illuminate these impacts but are understudied. Future work should extend preliminary explorations of such data (e.g., Merat et al., 2012; Radlmayr et al., 2018). There is an additional need for large time-series datasets containing driver steering and pedal input, vehicle kinematics, driver glance behavior, and information on the surrounding traffic. Such datasets are essential for model validation as illustrated in recent naturalistic data analyses (e.g., Markkula, Engström, et al., 2016).

Findings from the review of driver models

The review of driver models builds on several prior reviews in this area, specifically the work of Markkula et al. (2012) and Saifuzzaman and Zheng (2014). Markkula et al. (2012) reviewed near-collision driver models including models of avoidance by braking, steering, and a combination of braking and steering. The review identified several uses of models, (including the approach discussed in the Introduction of this article; see Figure 2), promising directions for future model development, and model limitations. In particular, they identified delayed constant deceleration models (which are a subset of the probabilistic response models described in Table 11), braking models including satisficing behavior, and steering models that do not include a desired collision avoidance path as promising for future development. Beyond these findings, the authors suggested that there is a need for more detailed driver braking models, and for formal model validation processes that critically assess the degree to which driver models replicate observed driver behavior. Saifuzzaman and Zheng (2014) echoed this sentiment. They identified a need for car following models that incorporate multiple human factors and data collection methods that collect information on drivers' psychological state, perception, and cognitive function. Finally, they advocated for analyses that rank human factors by their impact on car following (i.e. driver braking behavior). This review's approach—using empirical findings to guide model selection—follows the recommendations of both prior reviews. It extends on the prior work through the coverage of models proposed since the publication of the earlier reviews and notably covers evidence accumulation models and cybernetic models of steering behavior. The approach and reviewed models are summarized below along with future work.

Key factors of models of driver take-over

The finding that drivers often qualitatively perform similarly between manual and automated driving is important as it suggests that current models of manual driving may be extended to modeling take-overs, with extensions to consider the delays associated with the take-over process. Furthermore, the finding that TTC at the take-over request (or automation failure) has a significant effect on take-over time, post-take-over braking and steering behavior, and the decision to steer or brake, suggests that models that take into account scenario kinematics and urgency (e.g. visual angle models) should be preferred to models that depend on other cues such as brake-light activation. Evidence accumulation models are particularly promising as they explicitly model the empirically observed linear relationship between mean and standard deviation of take-over times (observed in Zhang et al., 2018). Beyond this relationship, Engström, Markkula, and Merat (2017) demonstrated that evidence accumulation braking models can incorporate human states such as cognitive distraction. Similar modifications may be applied to integrate various types of evidence (e.g., take-over alerts) and other driver factors (e.g., fatigue and alcohol impairment) that this review has identified as influential factors.

In the context of steering models, hybrid open-loop (e.g., Markkula, Boer, et al., 2018; Martínez-García et al., 2016) and cybernetic approaches (e.g., Nash & Cole, 2018) appear to be promising directions for future work given their ability to capture driver responses in emergency situations and the ability of cybernetic models to capture behavior driven by the neuro-muscular system. This latter mechanism may be important given the influence of the physical process of disengaging from handheld devices on take-over performance (observed by Wandtner et al., 2018a). However, significant additional work is needed to integrate influential factors on take-overs with these approaches. Further, it is still not clear if the additional complexity of these models would result in improved predictive capability.

In a similar vein, the review of driver evasive maneuver decision making suggests that there is a need for process models of driver decision making. The statistical modeling approaches discussed in this review highlight that visual angle is a powerful cue in driver decision-making. This finding is supported by the empirical observations (Gold et al., 2017). The common thread of visual angle throughout models of braking, steering, and decision making suggests that modelers in search of a single model to capture take-over behavior may benefit from a focus on visual-angle models.

Current models of driver take-over and research needs

The review highlighted two comprehensive process models of take-overs (Markkula, Romano, et al., 2018; Seppelt & Lee, 2015). Both models capture some, but not all of the requirements developed in this article. These models appear to be a promising direction for future modeling work, however, challenges remain. Future work in models of take-overs, whether they build from these initial models or pursue concepts discussed in prior sections, should pursue integrating the various factors that significantly influence take-over performance. Particular areas of focus should include the impact of handheld secondary tasks and take-over request modalities, as both factors are likely to be directions for future design work and possibly regulations. Besides these findings, there is a need for formal, controlled validations of model performance against specific criteria, for example in terms of safety outcomes. In addition, as the earlier modeling reviews have highlighted, it is critical to validate these models against actual driving behavior. As such, this review represents a promising practical direction, but it must be complemented by more formal validation analyses.

Practical contributions

Automated driving take-overs are a complex task involving physical and cognitive actions. This article distills this complex task into a set of influential factors and provides a practical roadmap for future empirical studies of take-over behavior. Researchers can use this work to design studies and identify baselines for driver performance. Beyond these findings, this review identified a set of promising driver models for future development. These models address concerns in earlier work regarding the inclusion of human factors in models of driver behavior and represent promising directions for future model development. Stakeholders can use these findings to identify starting points for their own modeling work. Thus, this article represents a step toward designing more accurate driver models.

Conclusions

We reviewed two expanding bodies of literature, empirical work on automated vehicle take-overs and driver modeling. The empirical work on automated vehicle take-overs indicates that the take-over time budget, secondary tasks, take-over request modalities, driving environment, and driver factors influence take-over performance. The empirical data on take-over behavior align to a large extent with what has been found in the past for manual driving, suggesting that existing models of manual driving provide suitable starting points for take-over models. The driver modeling literature did not identify an existing approach to capture all factors affecting take-overs but found promising initial directions, specifically those focused on the looming effect and evidence accumulation. Future work is needed to develop these models and provide more specificity of the impact of influential factors on take-over performance.

Key points

- Take-over time budget, repeated exposure to take-overs, presence of a take-over request and handheld secondary task significantly influence take-over time.
- Take-over time budget, repeated exposure to take-overs, presence and modality of a take-over request, driving environment, secondary task engagement, alcohol and fatigue impact post-take-over control.
- Drivers respond similarly between manual driving emergencies and automated vehicle take-overs although automation causes an additional delay.
- Evidence accumulation models represent a promising direction for take-over modeling but will require additional development to account for the factors that influence take-over.

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