Analysing Variables Associated with Driver Reaction during the Transition from Automated to Manual Driving

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***Abstract*—With the increasing development and implementation of Automated Driving Systems (ADS), understanding driver reactions during the transition from automated to manual driving has become a critical research area. The transition from automated to manual driving is a challenging task that requires the driver to take over control of the ADS-equipped vehicle in a safe and timely manner. Previous studies have identified various variables associated with driver reactions, but a comprehensive classification is lacking. This paper addresses this gap by systematically identifying and classifying the independent and dependent variables that affect drivers' reactions in ADS-equipped vehicles during the transition from automated to manual driving. This is achieved through an extensive review of major findings in the designs of driving simulator experiments in this field. Additionally, an analysis of five hundred on-road collision reports from 2014 to 2023 involving ADS-equipped test vehicles is conducted. Finally, a comprehensive overview of the identified dependent and independent variables from both studies, along with their synergies and shortcomings, is presented. The variables are categorised and mapped, highlighting key research gaps. The main research gaps were identified by comparing the variables extracted from reviewed papers with the statistical analysis in the DMV reports. Some gaps include the need for incorporating real-world scenarios into experiments, driver-initiated take-over requests and applying physiological measures to assess driver-centric factors. This detailed identification and classification of variables assists in designing a range of future experimental scenarios to assess drivers' reactions to the transition of control in ADS-equipped vehicles.**

***Index Terms*—Automated Driving System (ADS), ADS-equipped vehicles, Dependent/Independent variables, Driver reaction, On-road collision reports, Transition of control**

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This work is supported by the Engineering and Physical Sciences Research Council (Grant No. EP/R037795/1) and and UKRI Trustworthy Autonomous System HUB grant number: EP/V00784X/1.

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1. Introduction

A. Motivation

Road safety is a major concern for transportation users, vehicle developers, and insurance companies. With the advancement of technology, a number of safety-critical tasks in driving can now be managed by driving automation systems. On the journey toward the development of driving automation systems, various national organisations have defined different levels of Driving Automation [1]. In 2012, the German Bundesanstalt für Straßenwesen (BASt) defined four levels (in addition to level 0 for manual driving) [2], [3]. One year later, the National Highway Traffic Safety Administration (NHTSA) defined a similar classification for levels of driving automation [4]. In 2014, the Society of Automotive Engineers (SAE) outlined five levels of driving automation [5]. Their definitions were subsequently updated and adopted globally in 2016, 2018, and 2021 [6–8]. According to SAE J3016 – 2021, drivers take full responsibility for the safe execution of driving tasks throughout the journey in SAE Level 0 (no driving automation), SAE Level 1 (driver assistance), and SAE Level 2 (partial driving automation). At the same time, they can delegate specific control tasks to the vehicle (e.g., longitudinal and lateral motion control, lane changes based on the driver′s request). In SAE Level 3 (conditional driving automation), the vehicle can perform a dynamic driving task within a particular Operational Design Domain (ODD). SAE Level 4 represents high driving automation within a defined ODD. Hence, the driver does not need to continuously be prepared for a take-over request to ensure a safe journey, as the vehicle can automatically return to a minimal-risk condition if necessary. SAE Level 5 represents full driving automation in all driver-manageable on-road operating situations [8].

It should be noted that there is a difference between an Automated Driving System (ADS) and a Driving Automation System (DAS). In accordance with SAE J3016-2021, DAS carries out either a portion or the entirety of the Dynamic Driving Task (DDT) across all automation levels, including all SAE Levels. In contrast, ADS functions handle the full DDT, offer crash mitigation and avoidance features, and are compatible with SAE Levels 3 to 5 [8], [9]. ADS-equipped vehicles with SAE Levels 4 and 5 are not yet adequately developed for public use. However, ADS-equipped vehicles with SAE Level 3 are expected to see broader implementations in the future. According to the definition of SAE Level 3, there

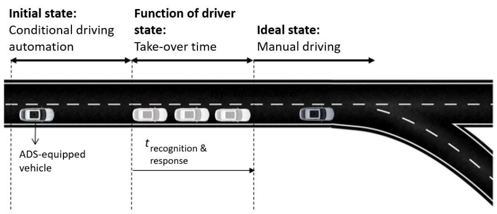

Fig. 1. Schematic illustration of a safe transition of control between the Driving Automation System (DAS) and a human user [11].

is no need for the user to drive the vehicle at all times, allowing the driver to perform non-driving-related tasks [10]. However, the driver should be ready to take control at short notice if the ADS reaches its limits. Figure 1 illustrates a secure transition of control from SAE Level 3 (conditional driving automation) to manual driving after the driver receives a take-over request. When the transition of control is triggered by the ADS, it becomes a challenging task since the driver might not be aware of the hazardous condition due to being immersed in a non-driving-related task and being out of the loop of control [12–15]. The transition of control in a vehicle with SAE Level 3 has attracted a significant amount of research [16–19]. Typically, in these studies, one or more variables are changed, and the effects of these independent variables on specific driver reactions, known as the dependent variables, are examined However, a comprehensive overview of the existing variables in this field is crucial.

Collisions involving vehicles equipped with driving automation systems are a concern for car developers and users. To date, the majority of commercially available vehicles with driving automation systems were SAE Level 2 and 1 (Mercedes-Benz opens sales of the first commercial ADS-equipped vehicle with SAE Level 3 in May 2022 [20]). As of May 2022, there have been six fatal collisions and numerous minor collisions involving vehicles equipped with driving automation systems at SAE Level 2 [21–26]. Statistics released by NHTSA in June 2023 indicate 17 deaths, with 11 of them occurring since May 2022 [27]. The cause behind at least one of these collisions was reported to be a failed execution of the take-over request, as the driver found it challenging to comprehend the situation and respond promptly, or the driver may have over-trusted the driving automation system′s ability to manage traffic situations [28]. Although ADS-equipped vehicles with SAE Level 3 have been commercialised since January 2023, there are currently no publicly available accident reports involving these vehicles. However, the California Department of Motor Vehicles (DMV) [29] has published collision reports involving research prototype ADS-equipped vehicles. Despite limitations in these reports, such as the vehicles being research prototypes and the drivers being trained safety drivers, analysing the variables that influence these collisions, particularly those occurring during transitions of control, can offer valuable insights to researchers aiming to prevent similar collisions in the future. Hence, we performed a comprehensive data extraction of the variables associated with these collisions by thoroughly reviewing and analysing all available reports from 2014 to 2023.

B. Contributions

Many empirical studies have been conducted to measure drivers' reactions during the transition of control from automated (predominantly SAE Level 3) to manual driving (SAE Level 0). Several literature reviews and meta-analyses [30–42] have investigated the effect of specific independent variables, such as alert types or take-over time budgets, on specific dependent variables, like reaction times or driving errors. These studies provide valuable insights but investigate a limited number of variables that restrict their scope. For instance, studies [30–34] conducted meta-analyses focusing on how non-driving-related tasks influence take-over times and driving performance. Shahini et al. [30] specifically investigated the effects of automation levels and non-driving-related tasks. In terms of driver-centric factors, Matthew et al. [35] conducted a meta-analysis investigating the effects of driver fatigue and distraction, Guo et al. [36] focused on the impact of fatigue on take-over behaviour, and Merlhiot et al. [37] investigated the effects of distraction and drowsiness on take-over performance. Gasne investigated the influence of one driver-centric factor, the driver's age, on take-over performance in automated driving [38]. Kim et al. identified research that studied how the user interface (an independent variable) affected take-over performance at higher levels of autonomy [39]. Jansen et al. reviewed the role of alert types as independent variables in take-over performance and emphasised the importance of multimodal alerts [40]. Weaver et al. in their meta-analysis focused on three independent variables (time budget, non-driving related task, and information support during the take-over) and assessed their effects on two dependent variables (take-over timing and quality measures) during conditionally automated driving [41]. In terms of dependent variables, Deniel et al. meta-analysis investigated the effect of a variety of independent variables on the gaze behaviours (dependent variable) during take-over [42].
Other studies [43–48] have conducted broader reviews, offering overviews of methodologies, models, or variables influencing take-over performance in ADS-equipped vehicles. For example, Zhang et al. reviewed empirical research and applied meta-analytic methods to examine the comprehensive set of factors influencing take-over time. They analysed take-over times from 129 experiments with SAE Level 2 automation or higher. Compared to our broader review, which also incorporates real-world incident data, Zhang et al. focused mainly on empirical research influencing take-over times, such as urgency, secondary task engagement, prior experience, and the type of take-over request [43]. Some reviews identified independent variables that affect driver situational awareness [44], [45]. Ansari et al. conducted a review on human-machine shared driving and highlighted that difficulties in recognising driver intent, estimating situational awareness, and modelling trust between the driver and automation system can delay the timely transition of control, sometimes leading to serious incidents [46]. McDonald et al. reviewed factors affecting take-over performance and proposed driver models for simulating transitions of control [47]. While their work offers general insights into modelling, our study provides a structured iden-

tification of variables to support future research. Soares et al. proposed a framework outlining primary strategies and experimental conditions; however, their work did not focus on detailed variable classification or the integration of real-world incident data [48].

However, to the best of the authors knowledge, these studies have not yet examined the variables influencing driver responses during the transition of control by combining findings from both academic literature and real-world incident data, such as DMV reports' data. Hence, we conducted a literature review to extract and analyse the variables influencing drivers' reactions (independent variables) and those used to assess these reactions (dependent variables) in empirical research. In addition, to provide an overview of real on-road situations, we carried out a comprehensive analysis of 546 DMV-reported on-road collisions involving test prototype ADS-equipped vehicles. The main contributions of this study are as follows:

- Identifying the independent and dependent variables associated with driver reaction during the transition of control based on past simulator-based experimental research.
- Determining the main variables linked to 546 collisions involving test prototype ADS-equipped vehicles, based on DMV reports for on-road collisions between October 2014 and January 2023.
- Mapping of the dependent and independent variables from the above analyses to identify existing gaps in this research domain.

C. Paper organisation

The rest of the paper is organised as follows: Section 2 highlights the main terminology used in this paper. Section 3 outlines the review methodology to identify and analyse studies on ADS-equipped vehicles. In Section 4, we extracted the key variables related to the reactions of users of ADS-equipped vehicles from the existing literature. Section 5 looks into the causes and conditions of on-road collisions by studying and analysing DMV reports involving test prototype ADS-equipped vehicles. Section 6 discusses the synergies in selecting dependent and independent variables for designing experiments with ADS-equipped vehicles, identifies gaps within experimental research, and points out potential avenues for future work. Conclusions are drawn in Section 7.

2. Terminology

The following terminology is used in this paper:

- *Level of Driving Automation*: The level of driving automation applies to the driving automation feature(s) engaged during any instance of on-road operation of an equipped vehicle. This includes: SAE Level 0 (No Driving Automation), SAE Level 1 (Driver Assistance), SAE Level 2 (Partial Driving Automation), SAE Level 3 (Conditional Driving Automation), SAE Level 4 (High Driving Automation), SAE Level 5 (Full Driving Automation) [8].
- *Driving Automation System*: This system executes all or part of the dynamic driving task across any level of automation, meaning it can support all SAE Levels [8].
- *Automated Driving System (ADS)*: ADS handles the entirety of the Dynamic Driving Task (DDT), possesses crash mitigation and avoidance capability, and supports SAE Level 3 to 5 [8].
- *ADS-Equipped Vehicle*: A vehicle equipped with driving automation features spanning SAE Levels 3 to 5 [9].
- *Driving Automation System-Equipped Vehicle*: A vehicle equipped with driving automation systems, i.e., SAE Level 1 to 5.
- *User/Driver*: This refers to the individual occupying the driver′s seat, responsible for the driving task when necessary across SAE Levels 0 to 5 [8].
- *Other Road Users and Components*: These include pedestrians, scooters, bicycles, vehicles (both with and without driving automation features), animals, and any other entities that may be present on or interact with the road in the vicinity of an automated vehicle [8].
- *On-Road*: Refers to publicly accessible roadways intended for use by all types of road users [8].
- *Transition of Control*: The process of switching from automated driving, as directed by the ADS, to manual driving overseen by the human driver (and vice versa) [49–52].
- *Take-Over Request*: A request from the ADS asking the human driver to resume control of the vehicle [53].

3. Review Methodology

The literature review was carried out systematically using the PRISMA method to provide a clear overview of the relevant research [54]. The search strategy involved utilising key academic databases, including Web of Science, ScienceDirect, SAGE, IEEE Xplore, ACM Digital Library, and PubMed. Specific search terms were applied to the title, abstract, and keywords. As permitted by the search engines, the initial search included one of the following expressions: 'automated driving systems', 'automated driving system', 'automated driving', 'autonomous vehicle', 'autonomous vehicles', 'Autonomy level 3', 'conditionally automated', 'driving automation', 'highly automated driving', or 'partially automated'. The results were then narrowed down by requiring that one of the following expressions also appeared: 'transition of control', 'transfer of control', 'take over', 'takeover', or 'take-over' (see Table A.1). The search covered studies published in journals and conferences from 2000 to the end of 2023 to capture the most recent developments in the field.

A. Inclusion Criteria

Studies were selected based on the following factors to ensure both relevance and quality: (1) Focus on automated vehicles and driver behaviour during the transition from automated to manual driving, particularly in driving simulator settings. (2) Published in peer-reviewed journals, conference proceedings, or other trusted sources. (3) Presentation of data and findings related to driver behaviours and reactions during the transition between automated and manual driving. (4) Inclusion of relevant keywords in the title, abstract, and keywords section of the paper.

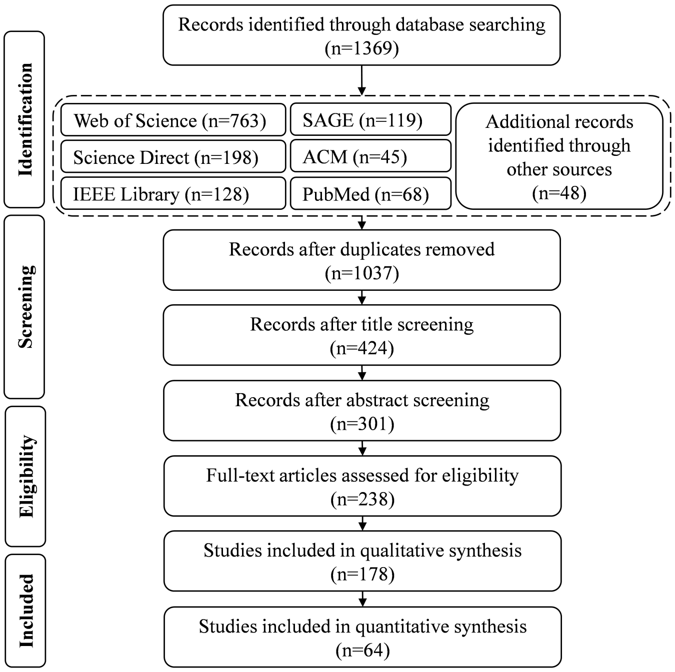

Fig. 2. Literature review based on PRISMA Guideline

B. Exclusion Criteria

Exclusion Criteria: Studies were excluded if they met any of the following conditions: (1) Lack of focus on automated vehicles or the transition from automated to manual driving. (2) Insufficient data regarding driver behaviour during the transition. (3) Published in non-peer-reviewed sources or publications with questionable credibility. (4) Review papers. (5) Non-English language papers.

C. Total Number of Studies Reviewed

A total of 1369 studies were identified in the initial search. The PRISMA diagram (Fig. 2) outlines the screening and analysis process. After removing duplicates, we reviewed 1037 articles. Initially, the titles were screened, resulting in 424 papers being selected for abstract review. Of those, 301 papers were chosen for full-text screening. Following the application of inclusion and exclusion criteria, the final dataset that met the predefined criteria consisted of 178 studies for qualitative analysis and 64 studies for quantitative analysis. Table 1 shows the details found after reviewing the selected papers.

4. Variables Extracted from Driving Simulator Studies

A driver's safe and timely response to the take-over request in hazardous situations is a concern when designing an ADS [55]. We have identified independent variables from experimental scenarios at SAE Level 3 (and higher) that may impact a user's take-over performance during the transition of control. In addition, we have pinpointed dependent variables that can be used to assess these impacts.

A. Independent variables

Table 1 provides an overview of the independent and dependent variables from experiments defined in the reviewed papers. Certain independent variables were frequently analysed in driving scenarios. For instance, many experiments focused on assessing the impact of different alert types [56–65], take-over time budgets [47], [55], [66–69], and various non-driving-related tasks [57], [59], [70–75]. Other, less-frequently analysed independent variables include training and system knowledge [76–79], the driver's cognitive and emotional state [62], [80–83], the age of the drivers and driving history of the drivers [71], [84–86], environmental factors such as road conditions [87] and weather conditions [16], [75], and the duration of the automated driving [83], [84]. A comprehensive list of independent variables is as follows (see also the second column of Table 1):

1) Alert type (TOR modalities): We have categorised the alert types used to inform the drivers to resume manual driving into three main classes: unimodal, bimodal, and multimodal alerts (see column six in Table B.1). Unimodal alerts consist of Auditory (A), Visual (V), and (vibro)Tactile (T) alerts. Specifically, unimodal auditory alerts can either be Auditory Vocal (AV) or Auditory Non-Vocal (ANV). Bimodal alerts include Auditory-Visual (A-V), Visual-(vibro)Tactile (V-T), and Auditory-(vibro)Tactile (A-T). Meanwhile, multimodal alerts incorporate all three types of alerts, i.e., Auditory-Visual-(vibro)Tactile (A-V-T). Based on the reviewed papers, Fig. 3 demonstrates the distribution of unimodal, bimodal, and multimodal alerts. The data indicates that AV alerts are used in 44% of all reviewed papers, while A and V alerts are used in 23% and 11% of all research, respectively. The (vibro)tactile alerts were investigated in only 22% of all reviewed papers. Within this category, 8% investigated T alerts, 8% looked into A-T alerts, 4% examined V-T alerts, and 2% explored A-V-T alerts. It is evident that take-over request modalities have a meaningful effect on take-over performance. For instance, Lee and Yang [88] showed that drivers had the best performance when prompted to resume control by a multimodal A-V-T alert, and had the poorest response by unimodal visual alert. The theoretical foundation helps explain why multimodal alerts outperform unimodal ones in take-over performance. According to the model proposed by Parasuraman et al., enhancing the level of informational support during a take-over request can lead to improved take-over performance [89]. The model describes the stages of human information processing—sensory input, perception and working memory, decision-making, and response selection—while drawing parallels to similar functions in automated systems: information acquisition, analysis, decision and action selection, and execution. The effectiveness of different TOR modalities aligns with this model, as each alert type engages different sensory and cognitive pathways. For example, multimodal A-V-T alerts enhance informational support by engaging multiple sensory channels, facilitating better sensory processing and working memory integration, which is critical for timely decision-making and response selection. In contrast, unimodal alerts like visual alerts may not provide sufficient informational support, leading to delayed or suboptimal responses.

2) Take-over time budget: When a take-over request is initiated, the driver needs time to regain their driving capability [91]. The take-over time budget is defined as the time

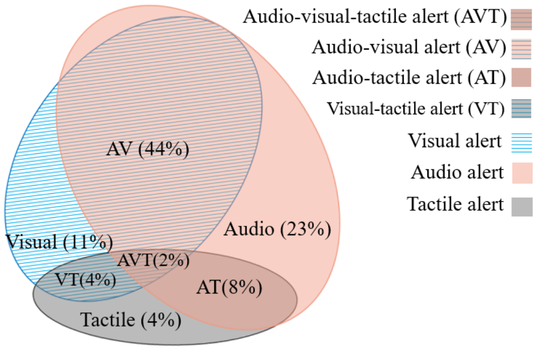

Fig. 3. Distribution of alert types in the literature discussed in Table B.1. Data visualisation with area-proportional Euler and Venn diagram Using ellipses (eulerAPE) [90].

remaining until a collision/conflict after the initiation of the take-over request [47]. Drivers are generally believed to be capable of meeting take-over requirements within a 7-second of take-over time budget [92]. However, Ito et al. [93] argued that a 5-second take-over time budget is sufficient for a safe transition of control. As shown in Table 1 take-over time budget was typically set between 6 and 8 seconds. However, some researchers allowed only 2 seconds for the take-over time budget, while in a few scenarios, it was extended to 20 seconds. Studies have indicated that take-over time budgets have a meaningful influence on driver′s take-over quality. A shorter take-over time budget usually leads to a reduced take-over duration and compromises the quality of the take-over [94], [95]. The take-over time budget significantly impacts the quality of a driver's response. Shorter budgets often result in rushed responses and diminished take-over quality [94], [95]. Conversely, a longer time window improves response quality by enabling drivers to reacquire situational awareness (SA), a critical factor highlighted by Endsley's situational awareness theory [96]. Endsley's model posits that regaining SA involves three stages: perceiving critical information (Level 1 SA), comprehending its significance (Level 2 SA), and projecting future states (Level 3 SA). A sufficient take-over time budget allows drivers to progress through these stages, enhancing decision-making and execution during transitions of control. This relationship is also supported by the out-of-the-loop (OOTL) performance problem discussed by Endsley and Kiris. Prolonged disengagement from active driving diminishes a driver's ability to monitor and predict traffic dynamics. By increasing the take-over time budget, drivers are better positioned to recover from OOTL states, improving both safety and performance during control transitions [96]. Empirical findings reinforce this theoretical framework. Pipkorn et al. [55], using driving simulators, demonstrated that drivers provided with more lead time before a take-over request exhibited safer responses. Similarly, Vlakveld et al. [69] emphasised that a driver's ability to detect hazards—an element of situational awareness—improves with additional time for transition. These results underline the importance of adequate take-over time budgets in supporting the reacquisition of situational awareness, thereby ensuring safer and more effective driver responses.

3) Non-driving-related task: In SAE Level 3 driving automation, as mentioned earlier, users can engage in non-driving-related tasks. These tasks can disengage the driver from actively controlling the vehicle. Most of these non-driving-related tasks in the literature require high cognitive and visual attention. However, some are only minor distractions, such as drinking water [97], or a cognitive but non-visual task [57], like engaging in verbal communication [70], [71]. Wandtner et al. [81] found that handheld non-driving-related tasks can significantly extend take-over time. Gold et al. [57] showed that different non-driving-related tasks influence take-over performance variably. For instance, in a high cognitive demand situation, a cognitive non-driving task has a greater impact compared to routine and straightforward scenarios. In simpler situations, motoric non-driving-related tasks had the most significant effect on take-over performance. According to Multiple Resource Theory, the brain has a finite pool of attentional resources that are distributed across different tasks. When drivers perform non-driving-related tasks that require similar cognitive resources as the driving task, the demands on attention can exceed the available cognitive capacity. This can result in slower responses and impaired performance, particularly if a sudden take-over is requested [30], [98].
Other studies have explored the impact of non-driving-related tasks on take-over performance. Zeeb et al. found that such tasks can increase lane deviation, reducing take-over quality [72]. While cognitive and visual demands generally influence performance, research by Erikson and Stanton and Ko and Ji indicated that the type of specific visual task does not significantly affect take-over time [51], [99]. Yoon et al. similarly concluded that non-driving-related tasks influence take-over time but do not interact significantly with alert type [100]. Radlmayr et al. noted that tasks like the n-back test and the visual Surrogate Reference Task impose similar cognitive demands, though SuRT is associated with higher accident rates in heavy traffic [73]. These findings align with the notion that tasks competing for the same cognitive resources as driving are more likely to impair performance. Other researchers observed that drivers who perform non-driving-related tasks, deviate further from the lane centre, leading to reduced take-over quality [72]. However, Erikson and Stanton [51] and Ko and Ji [99] observed that the type of visual non-driving-related task does not significantly influence take-over time. This is consistent with findings from Zeeb et al. [72], who examined the impact of tasks like reading, writing, and watching a video on the take-over process. Yoon et al. [100] concluded that while non-driving-related tasks affect take-over time, the alert type and non-driving-related task type do not have a significant effect on each other. Further supporting these conclusions, Radlmayr et al. [73] showed that both the n-back non-driving-related task and the standardised visual Surrogate Reference Task (SuRT) similarly influence take-over time, although the SuRT results in more accidents in heavy traffic in simulator settings.

4) Training and system knowledge: Boelhouwer et al. [79] investigated whether understanding the limitations and functionalities of ADS could help drivers improve their take-over decisions. The study involved two groups of participants: one group received written instructions about ADS capabilities and limitations, while the other remained uninformed. The researcher concluded that providing information through written instructions (paper-based) is not sufficient. A combination of both theoretical and practical training is the most effective learning method for drivers in ADS-equipped vehicles. It has been shown by Sahai et al. [76] that different types of training affect the take-over performance. Three training sessions were conducted for the participants: paper-based, video-based, and practice-based. The research found that practice-based training notably decreased drivers' response time to urgent take-over requests. In another study, augmented reality and virtual reality programs were used to train inexperienced drivers. The results indicated improvements in both reaction time and overall take-over performance after the training sessions [77], [78]. This variation in training effectiveness can be understood through Endsley's theory of situational awareness (SA), which explains how drivers progress through three levels of awareness: perceiving critical system information (Level 1 SA), comprehending its implications (Level 2 SA), and projecting future states (Level 3 SA). Effective training enhances drivers' ability to perceive and interpret key information about ADS functionalities and limitations, forming a foundation for quicker and more accurate take-over decisions.

Chen et al. [85] looked into the impact of driving experience (categorising drivers as inexperienced or experienced) on take-over quality. They found that novice drivers drove significantly less stable when performing conflict manoeuvres. Furthermore, longitudinal control, compared to lateral control, was more affected by driving experience. However, no significant differences were observed between inexperienced and experienced drivers concerning minimum time to collision and take-over time.

5) Driver-centric factor: The Transactional Theory of Stress and Emotion views stress as a reflection of the ongoing interaction between the operator (here, ADS-equipped vehicle user) and external demands or challenges [101], [102]. Fatigue, as a form of stress, signals that the driver is being overwhelmed by task demands, often resulting in reduced performance. Addressing fatigue and stress requires a holistic approach grounded in cognitive theory [35]. Desmond and Hancock identify two types of fatigue: active and passive. Their theory applies to various areas of transportation domains, including ADS-equipped vehicles [103]. Active fatigue is a stress-induced condition caused by excessive demands on cognitive abilities. Passive fatigue arises from underload and monotony, leading to reduced task engagement and diminished alertness. Saxby et al. conducted simulatalignor studies of ADS-equipped vehicles to empirically distinguish between active and passive fatigue. Their findings align with Desmond and Hancock's theory, showing that active fatigue, linked to a high workload, caused distress and a moderate loss of task engagement, whereas passive fatigue, associated with a low workload, led to a more pronounced decline in task engagement [104]. Matthew et al. demonstrated that automated driving often induces passive fatigue, resulting in a lasting loss of alertness when manual control is resumed [35].

Du et al. [80] investigated how the emotional state affects a driver′s take-over performance. They found that take-over time and quality were improved by positive valence, whereas high arousal didn't significantly affect take-over time (valence refers to the negativity or positivity of a stimulus, while arousal relates to the stimulus's capacity to make one feel sleepy or excited) [105]. Wiedemann et al. [17] explored how alcohol affects driver performance during a take-over. They found that a Blood Alcohol Content (BAC) of 0.08%, compared to 0.05%, had a greater negative impact on both longitudinal and lateral control, resulting in increased take-over time. Additionally, research by Samani et al. [84] demonstrated that the driver's age significantly influences reaction time during manoeuvres.

Beyond fatigue and emotional state, trust in automation influences the interaction between the user and automated driving systems. The theory of human trust in autonomy, which explores the nature of trust and how it evolves with system interactions, can help mitigate the risks associated with poor task allocation and decision-making [106]. While human drivers can articulate and report their trust, frequent interactions with the Driving Automation System may inadvertently increase driver workload and reduce situational awareness. Consequently, emerging research could focus on implicitly estimating driver trust through physiological signals, [15], [107].

6) Environmental factors: Heo et al. [16] researched the impact of environmental conditions such as sunny, snowy, rainy, and foggy weather and night on take-over performance. According to the study, environmental conditions have a significant influence on take-over time and other dependent variables (such as lane change time, maximum acceleration, subjective mental workload, etc). However, the research showed that using a specific alert type significantly reduced the effects of environmental conditions on take-over performances.

7) Level of driving automation: Carsten et al. explored how automation influences driver behaviour and found that higher levels of automation often lead drivers to focus more on non-driving-related tasks. This tendency can be explained through Multiple Resource Theory (MRT), which suggests that individuals allocate their limited attentional resources across tasks. When the high level of automation reduces the immediate demands of driving, these freed-up resources are more likely to be directed toward non-driving-related tasks, potentially impairing performance if a sudden need for manual control arises [108]. Samani et al. [84] investigated whether prolonged automated driving and repeated take-over requests have an impact on driving behaviour. Results indicated that the behaviour of the driver significantly changed after the transition of control and the behaviour didn't have a meaningful relationship with the length of automated driving and the number of take-over requests.

8) Movement preceding collision: Various studies have examined the movement preceding a collision, including factors like roadway conditions and traffic density. Samuel analysed different roadway environments, such as the Mullins centre, curves, work zones, and other vehicles in parked zones [87]. Zeeb explored conditions like faded lane markings and lane blockages from roadwork or broken cars [72], while Naujoks

focused on high-curvature sections and temporary lane markings [58]. Other researchers like Radlmayr and Radhakrishnan studied obstacles and road geometry, including urban vs. rural distinctions [109] [73]. Dambock considered missing lane markings, lane reductions (from 3 lanes to 2), and intersections on highways as independent variables impacting collision risk [110]. Korber, Du, and Gold examined various traffic densities, while Anih studied the effects of traffic density, aggression, and road geometry [70], [71], [111], [112].
Control theory provides a useful lens to understand driver responses to these conditions. Prospect theory models suggest drivers select acceleration or braking actions based on the utility of these actions, aiming to minimise risk or maximise safety [47], [113]. According to affordance theory, drivers' braking behaviour is driven by available actions and operates within a closed-loop control system, adjusting dynamically to environmental feedback [47], [114]. Driver steering models based on control theory are classified into three types: closed-loop, open-loop, and hybrid. In closed-loop models, drivers adjust steering to minimise errors based on real-time feedback. Open-loop models involve applying learned control inputs with periodic corrections. Hybrid models combine both approaches. These models can vary in what they control, optimization criteria, and the inclusion of neuro-muscular dynamics, referred to as cybernetic models [47].

9) Other road users: There are a limited number of studies focused on understanding ADS-equipped vehicle driver's behaviour when encountering other road users, such as pedestrians, cyclists, and motorcyclists. Pedestrians, in particular, present unique challenges as their behaviour can be unpredictable, including sudden changes in movement, jaywalking, or inconsistent walking speeds. For instance, Anih et al. examined the influence of environmental factors on AV safety using simulations, identifying high-risk elements like traffic flow, junctions, and pedestrian density. They highlighted differences in risk sensitivity between ADSs at Level 2/3 and Level 4, with distinct reactions to lane configurations and traffic flow [112].

B. Dependent variables

Table 1 presents dependent variables identified in the reviewed studies, and Table C.1 provides their corresponding definitions. The extracted dependent variables are split into two categories: objective measures and self-reported measures.

1) Objective measures: Objective measures are variables that can be consistently and impartially recorded and measured during the test. For this research, the objective measures were further divided into three subcategories of behavioural measures, vehicular measures and physiological measures.

Behavioural measures: A majority of behavioural measures are time-based and measure different reaction times to take-over requests. The most widely-used metric to quantify this is the Hands-on Reaction Time, which quantifies the time between the issue of the take-over request until the driver's hand placement on the steering wheel [58], [61], [68], [70], [72], [91], [115–117]. There are alternative metrics such as:

- Take-Over Time (TOT): Measures the time duration from the moment take-over is signalled until the manoeuvre is initiated [52], [56], [57], [61], [70–73], [83], [91], [115], [116], [118–120].
- Minimum TTC: Stands for minimum time to collision during the take-over phase [70], [80], [83], [111], [121].

Some other frequency-based behavioural metrics include:

- Distribution of Reaction Types: the percentage distribution of varied reaction forms e.g. braking [61], [64], [82].

Some stringent metrics are defined as the time required to activate a specific input in the car:

- Steer Initiate Reaction: Time period from take-over request until the driver initiates a steering turn [62], [82].
- Steer Turn Reaction Time: Time period from take-over request until the driver performs a steer turn (2 deg) [62].
- Pedal Reaction Time: Time until the driver begins braking or accelerating [62], [63], [115].
- Turn Signal Reaction Time: Time taken before the driver uses the indicator [60], [66], [92].

Some studies specify take-over reactions based on criteria that denote a manoeuvre in progress. These can be driven by specific steering turn angles, lane line crossings, or deviations from the lane's centre. For instance, the ar Avoid Reaction Time (i.e., the time until the deviation from the lane centre is greater than 1m [59], [62]), Minimum Time to Line Crossing [74]), and Lane Change Reaction Time (i.e. the time until the deviation from lane centre is ambient than 2m [62], [63], [82]). Another subset of behavioural measures relates to the number of driving errors recorded during the study. The errors can be related to unsafe lane selections or risky lane changes [110]. Among these types of error fall the Rate of Lane Change Error [61], [116], Choice of Lane [63], and Response Accuracy [119]. Further error types include Autonomy Mode's Confusion; that is, the driver believes the system is operating in a particular mode when, in reality, it is set to a different mode [97], System Warnings [97], and the amount of Collisions [67], [71], [91]. Additionally, some studies examined the driver's level of trust by intentionally probing the automated driving system's capabilities (testing the limits/boundaries) [97]. Another large subset of behavioural measures is gaze patterns, which focuses on where the driver looks. These measurements can be defined in a similar way to take-over reaction time, for instance, the time from the take-over request until when the driver turns their gaze to the area of interest, such as the side mirror or speedometer. Examples within this category include:

- Gaze Reaction Time: Defined as the duration from the take-over request until the driver's first glance away from non-driving-related tasks [83], [111], [115].
- Road Fixation Time: The duration from the take-over request to the driver's initial road focus [116], [122], [123].
- Side Mirror Gazing Time: The time from the take-over request to the driver's first side mirror glance [66], [115].
- Speedometer Gazing Time: The time from take-over request to the driver's speedometer check [115].
- Average Duration of Gazes: The average time a driver's gaze remains on an area of interest per glance [83].

- Cumulative Duration of Gazes: Combined duration a driver looks at an area of interest [74], [83], [91], [121].
- Maximum Duration of One Gaze: The longest duration a driver maintains their gaze on an area of interest in a single instance [83].

In addition, gaze metrics can be frequency-based, such as the total number of times a driver looks towards a specific area of interest [63], [74], [83], [87], [91], [121]. Another metric is the Percent Road centre which calculates the number of times the driver's gaze is centred on the road within a specified timeframe [124], [125]. There are also statistical gaze metrics, for instance, the Distribution of Gazes across an area of interest [63], [74], [75], [120], and Horizontal Gaze Dispersion, which quantifies the deviation in horizontal gaze positioning [70].

Vehicular measures: Vehicular measures are quantities that describe the state of the vehicle in relation to the road and other road users and components. These measures include position (both lateral position and headway distance), speed, acceleration (lateral and longitudinal), and the steering wheel angle and rate. The vehicular measures are determined by calculating the minimum, maximum, mean or standard deviation of these collected quantities. Specific measures in this category include:

- Standard Deviation of Lateral Displacement: This measures the standard deviation of the lateral position of the ADS-equipped vehicle after a take-over request has been issued [52], [72], [115], [120].
- Maximum Lateral Position: This refers to the maximum deviation of the vehicle from the lane's centre after the take-over request [58].
- Minimum Headway Distance: The distance between the ADS-equipped vehicle and the leading vehicle or conflict during the take-over scenario [59], [75], [84], [126].
- Maximum Steering Wheel Angle: This represents the maximum steering wheel angle during the take-over period [56], [124].
- Mean Speed: This is the average speed of the ADS-equipped vehicle during the take-over phase.
- Minimum Speed: Refers to the vehicle's minimum speed after the take-over request [56], [124].
- Standard Deviation of Steering Angular Rate: This measures the standard deviation of steering angular velocity post-take-over request [51], [52].
- Maximum Lateral Acceleration: The highest lateral acceleration of the vehicle after the take-over request [57], [71], [72], [82], [83].
- Maximum Longitudinal Acceleration: The maximum longitudinal acceleration of the vehicle during the take-over period [70], [71], [83], [116].
- Maximum Resulting Acceleration: This measures the maximum combined acceleration of the vehicle during the take-over, including both longitudinal and lateral accelerations [61], [116], [117].

Among these measures, the two most widely used metrics in research are the Standard Deviation of Lateral Position [51], [58], [72], [115], [117], [119], [120], [124] and the Maximum Longitudinal Acceleration [57], [61], [66], [70], [71], [73], [82], [83], [92], [116]. There are also alternative dependent variables highlighted in the reviewed papers, such as the Distribution of Reaction Types among behavioural sensors [61], [64], [66], [82], [92], [125] or the Graphical Representation of Vehicle Trajectories in specific situations among vehicular sensors [61], [66], [110], [127]. Other variables include the Percentage of Braking after a take-over request (no action, off throttle, braking) [63], [68], [125], the acceleration behaviour (indicating the number of times the acceleration pedal is engaged) [63], and the Speed Profile which evaluates whether the driver is moving too fast or too slow [63].

Physiological measures: Physiological measures quantitatively assess characteristics associated with the functioning of the human body. Physiological measures include Electroencephalogram (EEG), Electrocardiogram (ECG), Electrooculogram (EOG), Heart Rate Variability (HRV), Photoplethysmography (PPG), Galvanic Skin Response (GSR), Electrodermal activity (EDA), Skin Conductance Response (SCR), and Respiration (RESP), etc. For example, electroencephalogram (EEG) brain signal measurements can quantify a driver's reaction to a take-over request [128]. EOG data closely reflect visual attention [129]. HRV signals provide insights into the driver's workload [130], stress [131], and drowsiness [132]. GSR is an indicator of stress, workload and emotional arousal, as changes in GSR can signal sweating on the hands [133].
Meteier et al. collected ECG, EDA, and RESP data from driving simulator experiments to predict driver states and classify driver workload levels during conditionally automated driving [134–136]. Pakdamanian et al. used GSR and HRV physiological measures to predict a driver's intention, timing, and quality of take-over while engaged in non-driving-related tasks [128]. Ayoub et al. used GSR and HRV metrics during a driving simulator study to predict real-time driver trust in conditionally automated vehicles. Their results demonstrated the potential for real-time trust prediction, providing insights for designing in-vehicle systems that adjust driver trust to improve interaction with ADS-equipped vehicles [137]. Radhakrishnan et al. measured physiological responses including HRV, SCR, and EDA to assess driver discomfort across different levels of driving automation, driving environments, and road conditions [109]. Du et al. examined drivers' take-over performance during automated driving by collecting physiological data, including HRV and GSR. The study involved drivers performing non-driving-related tasks and subsequently taking over control of the vehicle. They predicted take-over performance under varying levels of cognitive load [138]. Few studies focused on EEG measures. Pakdamanian et al. used EEG as a physiological measure to understand which type of alert led to safer driver take-over behaviour. The results showed greater engagement and safer take-over behaviour with the auditory-visual alert compared with the unimodal auditory alert. However, the authors stated that their findings were preliminary since the study only involved two participants. Lee et al. [88] analysed the influence of the various combinations of alert types on brain signals. Their analysis recommended the use of multimodal alerts. They stated that their findings were consistent with previous studies [139], where the unimodal visual alert was found to be less effective

due to prolonged reaction times. Zhou et al. [140] studied the correlation between EEG signals and the vigilance of ADS users. Reaction time, closely related to EEG signals, was used as a measure of vigilance. Their analysis predicted reaction times using EEG signals and compared them with actual experimental results, finding that EEG could act as a proxy measure for reaction time. Researchers also worked on finding a correlation between the situational awareness of drivers and EEG signals [141]. They correlated EEG signals with primary variables such as reaction time. Depending on whether the function of reaction time was longer or shorter than a specific threshold, EEG signals were labelled as indicating either poor or good situational awareness. They developed this model using an EEG data set provided by Cao et al. [142]. Some other research has shown that brain activity measurements can be used to estimate the complexity of non-driving-related tasks [143]. In a study by Van Miltenburg et al. [144], drivers in a simulator were distracted by non-driving-related tasks of varying difficulty levels while simultaneously being asked to take control of an ADS-equipped vehicle. It was demonstrated that EEG data could reflect participants' distraction levels. However, they reported that EEG data are not able to reliably predict driving performance during a take-over scenario.

2) Self-reported measures: Self-reported measures capture the perception of driving quality based on the user′s feelings, opinions, attitudes, and beliefs. These can be gathered through a questionnaire where drivers rate their subjective opinion on a defined scale for each question [145–147]. Some researchers use standard questionnaires such as the NASA-TLX which assesses subjective workload [52], [60], [62], [121], the Situation Awareness Global Assessment Technique questionnaire (SAGAT) [67], [74], and Situation Awareness Rating Technique questionnaire (SART) [67]. Other self-reported measures extracted from reviewed papers include:

- Mental Workload: a 16-point scale ranging from "not demanding" to "very demanding" [115].
- Comfort of Take-Over [64], [64], [110].
- Ease of Take-Over: assessment of the take-over task as easy, stressful, or overwhelming [68].
- Take-Over Performance: self-evaluation of performance in hazardous situations [68].
- Driving Performance: safety perception using human-machine monitoring state evaluation interfaces [56].
- Performance in Non-Driving-Related Tasks: assessing engagement in tasks unrelated to driving [68].
- Take-Over Strategy: self-explanation of how the take-over was executed [68].
- Take-Over Readiness: the driver's state of preparedness when a take-over request was made [47], [111].
- Controllability: personal perception of vehicle control on an 11-point scale [73].
- Criticality: driver's perception of the criticality of the current situation [73].

For more details and definitions, refer to Table C.1.

Table 3, derived from Table 1, summerises the distribution of independent and dependent variables across 64 studies, and Table 4, presents the number of combinations of variables studied in these studies. Looking at Table 4, combinations of independent and dependent variables with lower representation might highlight a gap in research and warrant further investigation to evaluate their impact.

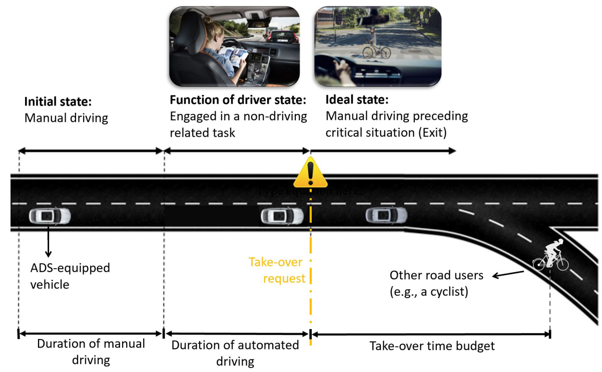

Fig. 4. Schematic of driving simulator study parameters: manual and automated driving periods, take-over time, driving speed, participant count, road type, non-driving related tasks, and alert/notification types [148], [149].

C. The categorisation of independent and dependent variables

The categorisation of independent and dependent variables was guided by their roles in influencing or representing driver behaviour. Independent variables, such as alert type and take-over time budget, were identified as factors shaping the context of driver reactions, while dependent variables, like take-over time or eye movement, captured drivers' behavioural or physiological responses. This classification aligns with cognitive models of attention and workload, providing a robust theoretical basis. Variables were drawn from peer-reviewed studies, simulator experiments, and real-world collision reports, ensuring both theoretical and practical relevance. Cross-referencing DMV data with simulator-based findings further enhanced consistency. The framework was validated through alignment with established methodologies, systematic mapping across experimental and real-world contexts, and the organisation of dependent variables into objective and subjective measures, ensuring clarity, reliability, and comprehensive coverage.

D. Other crucial parameters in driving simulator studies

Table B.1 provides an overview of the major parameters commonly used in designing driving simulator experiments in this field. It is worth noting that in some studies, these parameters were used as independent variables. However, in most driving simulator studies, they are essential components of the design process (see Fig. 4). The extracted parameters include: (1) duration of manual/automated driving, (2) total duration of the experiment, (3) take-over time budget, (4) speed during manual/automated driving, (5) number of participants in the experiment, (6) road type, (7) assigned non-driving-related tasks, and (8) alert/notification type.

As summarised in Table B.1, a typical scenario in these studies consists of a combination of manual driving periods and intervals of automated driving. In order to construct similar experiments for the analysis of the reaction of the ADS-equipped vehicle users, the duration of both manual and automated driving are key; each scenario can consist of multiple sections of each type of driving. In many studies, the duration of manual driving was not specified. However, there are experiments in which one section of manual driving can last up to 10 minutes [56]. A single section of driving in automated mode spans anywhere from a few seconds to 30 minutes. The total duration of driving simulator experiments ranged from 2 to 135 minutes with a mean value of 47 minutes.

Most of the simulated scenarios were set on highways, which means the targeted speed for manual driving typically ranged from 80 to 120 km/h. Automated driving speeds were similar, though 13 studies allowed for speeds under 80 km/h in automated driving. Investigation of the road types shows that two and three-lane roads were the most commonly simulated. Only four studies centred on a single-lane (rural) scenario, while five or six-lane scenarios were used in four other studies. The number of participants in each study varied between 12 and 89, with a mean value of 38 participants.

TABLE 1: INDEPENDENT AND DEPENDENT VARIABLES IN REVIEWED PAPERS

No.	Independent Variables	I1	I2	I3	I4	I5	I6	I7	I8	I9	Dependent Variables	D1	D2	D3	D4	Author (Year)	Ref
1	(1) NDRTs: writing email, watching video, taking breaks with eyes closed, (2) Duration of engagement in NDRT.		✓	✓							(1) HRV, (2) NASA-TLX, (3) Steering angle, (4) SD of vehicle lateral position.		✓	✓	✓	Zhang (2023)	[150]
2	(1) Two TO scenarios, (2) NDRT modalities.		✓	✓							(1) Interview (scene-description to assess situational awareness), (2) Interview (fatigue)	✓		✓		McKerral (2023)	[151]
3	(1) TOT budgets, (2) Criticality of the situation		✓								(1) RT, (2) TO decision.	✓		✓		Leitner (2023)	[152]
4	(1) TO types (partial TO, assisted TO, full TO							✓			(1) Min TTC, (2) Lane deviation, (3) Success rate, (4) Usability	✓	✓	✓		Gruden (2023)	[153]
5	(1) TO scenarios: control condition, false alarm condition, miss condition. (2) TOT budgets.	✓	✓								(1) Driver trust, (2) GSR, (3) HRV, (4) Eye movement.	✓		✓	✓	Ayoub (2023)	[137]
6	(1) Lighting (morning, daylight, night), (2) Weather (clear, cloudy, raining, fog), (3) No. of pedestrians (10, 20, 30), (4) Traffic density, (5) Traffic aggression, (6) Road geometry							✓	✓	✓	Risk factors, (1) Harsh accelerations/braking, (2) Inverse TTC (3) Inverse time headway.	✓	✓			Anih (2023)	[112]
7	(1) Manipulation of relaxation, (2) Presence of a passenger, (3) Verbal NDRTs (backward counting) (4) NDRT: visual and auditory tasks (N-back task), (5) Fatigue, (6) Rural vs. urban, (7) Alert types (visual, auditory, haptic).	✓		✓		✓			✓		(1) RT, (2) Steering wheel angle, (3) Questionnaire (Unipark, NASA-TLX), (4) Electrocardiogram, (5) Electrodermal activity, (6) Respiration.	✓	✓	✓	✓	Meteier (2023)	[134]
8	(1) Environmental factors (sunny, rainy, snowy, foggy, night-time), (2) TOR cues (augmented reality and smartphone alert).	✓					✓				(1) TOT, (2) Lane change RT, (3) TTC, (4) Max Acc, (5) Subjective mental workload	✓	✓	✓		Heo (2022)	[16]
9	(1) TOR lead time, (2) TO frequencies, (3) Scenario type.		✓						✓		(1) TO criticality, (2) Skin conductance, (3) Heart rate, (4) Gaze behaviour, (5) Min TTC.	✓			✓	Yi (2022)	[154]
10	(1) Driving mode (Level 2 vs. Level 3), (2) TOT budget (for Level 3), (3) Conflict scenario (Level 2 and 3).		✓					✓			(1) Hands-on RT, (2) First glance to human-machine interface, (3) First glance forward, (4) Automation deactivate, (5) Onset of last on-path glance, (6) Steering RT to conflict object, (7) Steering RT to lead-vehicle cut-out.	✓	✓			Pipkorn (2022)	[55]
11	(1,2) Auditory verbal driving-related feedback with/without beep, (3) Verbal non-driving-related feedback, (4) No audio feedback.	✓		✓							(1) Gaze behaviour, (2) RT, (3) NDRT performance, (4) Trust in the auditory interface.	✓		✓		Cohen-Lazry (2022)	[155]
12	(1) Handover procedures: (I) Immediate handover, (II) Delayed handover, (III) Delayed handover with blind-spot assist, (IV) Assisted handover. (2) Time interval: (I) 2.0 s, (II) 7.0 s, (III) 15.0 s.		✓								(1) Steering torque, (2) SD of Lateral position, (3,4) Percentage of gaze toward road centre/rear mirror, (5) Time to lane crossing, (6) Gaze movement, (7) manoeuvre duration, (8) Crashes, (9) Workload, (10) Comfort.	✓	✓	✓		Maggi (2022)	[156]
13	(1) In-vehicle agent voice dominance to the driver (dominant, submissive).	✓									(1) Driver situation awareness, (2) Emotional regulation, (3) Trust, (4) Willingness to adopt.			✓		Yoo (2022)	[157]
14	(1) Duration of automated operation, (2) Number of TOR in an automated operation, (3) Gender, (4) Age, (5) Years of experience, (6) Education, (7) Number of crashes, (8) Tickets in past 2 years, (9) Annual driving mileage.		✓		✓	✓					(1) RT, (2) Mean speed, (3) Max speed, (4) Max lateral speed, (5) Max acceleration, (6) Mean Acc, (7) Max deceleration, (8) Max lateral Acc, (9) SD of lateral positioning, (10) Min TTC, (11) Min headway distance, (12) Max heading error.	✓	✓			Samani (2022)	[84]
15	(1) NDRTs.			✓							(1) Lane position, (2) Steering angle, (3) Throttle and brake (4) Eye movement (5) HRV (6) GSR (7) Pre-driving survey (8) TOT.	✓	✓	✓	✓	Pakdamanian (2021)	[158]
16	(1) NDRT (with/without), (2) TOT budget, (3) Manual driving experience.		✓	✓	✓	✓					(1) Automation disengagement time, (2) TOT, (3) Min TTC, (4) Max longitudinal deceleration, (5) Max lateral Acc, (6) Resultant Acc.	✓	✓			Chen (2021)	[85]
17	Age: (1) Younger old (60-69 years old), (2) Older old (over 70 years old).					✓					(1) Motor readiness time, (2) TOT, (3) Indicator time, (4) min TTC, (5) Resulting Acc, (6) Steering wheel angle, (7) Hasty TO, (8) Collisions and critical encounters, (9) TO behaviour, (10) Attitude.	✓	✓			Li (2021)	[159]

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No.	Independent Variables	I1	I2	I3	I4	I5	I6	I7	I8	I9	Dependent Variables	D1	D2	D3	D4	Author (Year)	Ref
18	Type of training: (1) Paper-based, (2) Video-based, (3) Practice-based.				✓						(1) TOT, (2,3) Human-machine interface first glance RT/duration, (4) Road first glance RT, (5) Mirror first glance RT, (6) Workload, (7) Satisfaction.	✓		✓		Sahai (2021)	[76]
19	(1) Five TO situations with varying TOT budget.		✓								(1) Subjective criticality rating (SCA), (2) Effort-subscale of NASA-TLX, (3) TOT, (4) Max steering wheel position, (5) Max brake pedal position.	✓	✓	✓		Roche (2021)	[160]
20	(1) Level of driving automation (2) Road (rural, urban) (3) Road geometry (4) Obstacle (parked cars, road works, pedestrian refuge).							✓	✓		(1) Physiological responses (HRV, ECG, EDA) (2) Button presses.	✓			✓	Radhakrishnan (2020)	[161]
21	(1) NDRTs, (2) Traffic density, (3) TOR lead time.		✓	✓					✓		(1) HRV, (2) GSR, (3) Eye movement.	✓			✓	Du (2020)	[138]
22	(1) Emotional valence, (2) Arousal.					✓					(1) TOT, (2) Max resulting Acc, (3) Max resulting jerk, (4) Min TTC, (5) Emotional valence, (6) Arousal.	✓	✓	✓		Du (2020)	[80]
23	(1) Time headway, (2) Traction usage, (3) Vehicle dynamics.		✓						✓		(1) Criticality rating, (2) TOT, (3) Max deceleration, (4) Lane change frequency, (5) Collision frequency.	✓	✓	✓		Roche (2020)	[126]
24	(1) TOR procedure (1-step/2-step), (2) Visual TOR modality (text/text & pictogram), (3) Auditory TOR modality (tone/speech).	✓									(1) Intuitiveness, (2) Usefulness, (3) Attractiveness, (4) Appropriateness of the information.			✓		Brandenburg (2019)	[162]
25	(1) System information (has/has not).				✓						(1) TO decisions (yes/no).	✓				Boelhouwer (2019)	[79]
26	(1) Different NDRTs, (2) TOR modalities.	✓		✓							(1) Usefulness, (2) Safety, (3) Satisfaction, (4) Effectiveness, (5) TOT, (6) Hands-on time, (7) Time to fixation.	✓		✓		Yoon (2019)	[100]
27	(1) Playing a game on a tablet NDRTs, (2) Reading on a tablet NDRT, (3) No NDRT, (4) Manual/automated driving.			✓				✓			(1) Hands-on RT, (2) Gaze RT, (3) TOT, (4) Pedal RT, (5) Side mirror gazing time, (6) Speedometer gazing time, (7) Standard deviation of lateral lane position, (8) Controllability, (9) Mental workload.	✓	✓	✓		Vogelpohl (2018)	[115]
28	(1) Drive 40 minutes along public roads and highways in a Tesla Model SP90.					✓					(1) Occurrence of system warning, (2) Testing the boundaries of operational design domain, (3) Mode confusion, (4) Engagement in NDRT.	✓	✓	✓		Banks (2018)	[97]
29	Level of blood alcohol concentration: (1) No alcohol, (2) 0.05%, (3) 0.08 %.					✓					(1) TOT, TO quality: (2) SD of lateral position, (3) SD of steering wheel angle, (4) SD of velocity, (5) Min TTC, (6) Min headway to the broken down vehicle, (7) Criticality of the situation.	✓	✓			Wiedemann (2018)	[17]
30	(1) Different automation duration (5 min, 20 min), (2) Underload/overload conditions, (3) With/without NDRT.			✓		✓					(1) Gaze RT, (2) TOT, (3) Min TTC*, (4) Max longitudinal Acc, (5) Max lateral Acc, (6) Cumulative duration of gazes, (7) Average duration of gazes, (8) The Max duration of one gaze, (9) Number of gazes.	✓	✓			Feldhutter (2017)	[83]
31	(1) Videos of different duration (1.0 s, 3.0 s, 7.0 s, 9.0 s, 12.0 s, 20.0 s).		✓	✓							(1) Self-reported time sufficiency, (2) Self-reported task difficulty, (3) The number of placed cars, (4) Total distance error, (5) Total speed error, (6) Geometric difference, (7) Attention distribution, (8) Glance to the mirrors.	✓	✓	✓		Lu (2017)	[163]
32	(1) An auditory TOR, (2) A vibrotactile TOR.	✓									(1) Hands-on RT, (2) Steer initiate RT, (3) Steer turn RT, (4) Lane change RT, (5) Pedal RT, (6) Min intervention RT, (7) Workload, (8) Usefulness.	✓	✓	✓		Petermeijer (2017)	[60]
33	Out-of-the-loop manipulation: (1) No manipulation, (2) Light fog, (3) Heavy fog, (4) Heavy fog and visual task, (5) n-back task.			✓			✓				(1) Distribution of gazes.	✓				Louw (2017)	[75]
34	(1) Manual driving, (2,3) Automated driving with/without NDRT.			✓				✓			(1) SD of steering wheel angle, (2) SD of lateral position.		✓			Eriksson (2017)	[51]

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No.	Independent Variables	I1	I2	I3	I4	I5	I6	I7	I8	I9	Dependent Variables	D1	D2	D3	D4	Author (Year)	Ref
35	(1) Eight different patterns in the vibrotactile seat: (four static, four dynamic), (2) Three mental demands (low, medium, high).	✓		✓		✓					(1) Correct response rate of vibrotactile patterns, (2) Steer initiate RT, (3) Steer turn RT, (4) Lane change RT, (5) Gaze heading, (6) Head heading, (7) Subjective workload, (8) Usefulness, (9) Satisfaction.	✓	✓	✓		Petermeijer (2017)	[62]
36	(1) Manual driving, (2,3) Automated driving with/without NDRT.			✓				✓			(1) TOT*, (2) SD* of steering angular rates, (3) Subjective workload score.	✓	✓	✓		Eriksson (2017)	[52]
37	Driving condition: (1) Anticipated take-over, (2) Unanticipated take-over, (3) Manual driving.	✓						✓			(1) TOT, (2) SD of lateral position, (3) Distribution of gazes.	✓	✓			Dogan (2017)	[120]
38	(1) Age (> 60 and < 28 year-old drivers), (2) Verbal NDRT, (3) No traffic density, (4) Medium traffic density, (5) High traffic density.			✓		✓			✓		(1) TOT, (2) Min TTC, (3) Max lateral Acc, (4) Max longitudinal Acc.	✓	✓			Korber (2016)	[71]
39	(1) Mullins centre, (2) Curve, (3) Work zone, (4) Hiker, (5) Rotary, (6) Stop-controlled intersection, (7) Vehicles in the parked lane.								✓		(1) Anticipation of hazard by glance rate in the target zone.	✓				Samuel (2016)	[87]
40	(1) Zero traffic density, (2) 10 vehicles/km traffic density, (3) 20 vehicles/km traffic density, (4) Verbal NDRT, (5) Without verbal NDRT.			✓					✓		(1) Hands-on RT, (2) TOT, (3) Max longitudinal Acc, (4) Max lateral Acc, (5) Min TTC, (6) Horizontal gaze dispersion.	✓	✓			Gold (2016)	[70]
41	(1) All alert LEDs turn on, (2) Static light (half of the alert LEDs turn on to hint steering direction), (3) Moving light (a number of LEDs iteratively turn on to hint at steering direction).	✓									(1) Steer initiate RT, (2) Min TTC, (3) Subjective workload, (4) Cumulative duration of gazes, (5) Number of gazes.	✓	✓	✓		Borojeni (2016)	[121]
42	(1) Writing email NDRT, reading NDRT, watching video NDRT, (2) Faded lane markings, (3) Faded lane markings with a wind gust, (4) Additional lane, (5) Blocking of the ego-lane.			✓					✓		(1) Road fixation time, (2) Hands-on reaction time, (3) TOT, (4) Standard deviation of lateral position, (5) Max lateral Acc.	✓	✓			Zeeb (2016)	[72]
43	Three distinct TO scenarios involving a geometrically transformative steering wheel that adjusts its shape according to the selected driving mode.	✓									(1) Gaze reaction, (2) Road fixation, (3) Movement time, (4) Hands-on time, (5) Side mirror time, (6) TOT, (7) Rate of lane change error, (8) Max lateral Acc, (9) Max longitudinal Acc, (10) Max Acc.	✓	✓			Kerschbaum (2015)	[116]
44	(1) Three different urgency (notice, warning, danger), (2) 7 modalities (A**, V**, T**, A-V**, A-T**, V-T**, A-V-T**), (3) 2 scenarios (car to driver handover, driver to car handover).	✓									(1) Button press RT, (2) TOT (3) Response accuracy, (4) SD of lateral position.	✓	✓			Politis (2015)	[119]
45	(1) Three different NDRTs (supervising the advanced driving assistance system, reading, and watching video), (2) Single-stage hands-on request versus two-stage hands-on request.	✓		✓							(1) Driver drowsiness (yawning or eye closure), (2) Button press RT, (3) Car avoid RT, (4) Min headway distance.	✓	✓			Miller (2015)	[59]
46	(1) Caution and 6.0 s TOT* budget, (2) 4.0 s TOT budget, (3) 6.0 s TOT budget.	✓	✓								(1) Hands-on RT*, (2) Braking behaviour, (3) Comfort of TO, (4) Ease of TO, (5) TO performance, (6) TO strategy, (7) Performance in NDRT*.	✓	✓	✓		Walsh (2015)	[68]
47	(1) PEBL simple response time test (2) Multitasking test including suRT* NDRT.		✓	✓							(1) TOT (2) Eye tracking.	✓	✓			Korber (2015)	[118]
48	(1) Bimodal A-T** alert, (2) Unimodal auditory alert.	✓									(1) Pedal RT, (2) Lane change RT, (3) Braking behaviour, (4) Acc behaviour, (5) Choice of lane, (6) Speed profile, (7) Number of gazes, (8) Distribution of gazes, (9) Haptic feedback satisfaction.	✓	✓	✓		Telpaz (2015)	[63]
49	Reaction to a stationary vehicle in (1) Manual mode, (2) Automated mode, (3) when the user was reading text on an iPad.			✓		✓		✓			(1) Max lateral Acc, (2) Max longitudinal Acc, (3) Steer initiate RT, (4) Lane change RT, (5) Distribution of reaction types.	✓	✓			Louw (2015)	[82]
50	Four different TOR strategies (combination of mobile phone integrated/not integrated and brake jerk integrated/not integrated).	✓		✓							(1) RT, (2) Driver behaviour (video analysis), (3) Distribution of reaction types, (4) Comfort of the driver.	✓		✓		Melcher (2015)	[64]

continued …

…continued

No.	Independent Variables	I1	I2	I3	I4	I5	I6	I7	I8	I9	Dependent Variables	D1	D2	D3	D4	Author (Year)	Ref
51	(1) SuRT (visual-motoric NDRT), (2) Fill-in of text blanks (visual-motoric-cognitive NDRT), (3) Cognitive-motoric NDRT, (4) Cognitive NDRT, (5) No NDRT.			✓							(1) TOT, (2) Gaze RT, (3) Min/Max longitudinal Acc, (4) Min/Max lateral Acc, (5) Min TTC.	✓	✓			Gold (2015)	[57]
52	Three different TOR situations (1) Road blockage through roadwork, (2) Road construction sign or broken car with high traffic.	✓							✓		(1) Number of gazes, (2) Cumulative duration of gazes, (3) Amount of collisions, (4) TOT, (5) Hands-on RT.	✓				Zeeb (2015)	[91]
53	(1) Visual alert, (2) A-V** alert, (3) End of lines, (4) Temporary lines, (5) High curvature.	✓							✓		(1) Hands-on RT, (2) Max* lateral position, (3) SD* of lateral position.	✓	✓			Naujoks (2014)	[58]
54	(1) NDRT (2 states: yes/no), (2) Functionality (3 states: full, adaptive cruise control, and slow), (3) Interaction (3 states: none, drivers' safety device, and video).			✓				✓			(1) Cumulative duration of gazes, (2) Distribution of gazes, (3) Number of gazes (windshield, video image), (4) SAGAT questionnaire, (5) RT, (6) Amount of collisions, (7) Min time to line crossing.	✓		✓		Wulf (2014)	[74]
55	Graphical information during TOR (Augmented reality blue or red or none).	✓									(1) Gaze RT, (2) Road fixation time, (3) Turn signal RT, (4) Hands-on RT, (5) Side mirror gazing time, (6) TOT, (7) Rate of lane change errors, (8) Max lateral Acc, (9) Max longitudinal Acc, (10) Distribution of RTs, (11) Trajectories.	✓	✓			Lorenz (2014)	[61]
56	(1) Reduced width, (2,3) Fixed/Variable automated driving, (4) SD of lane position, (5) Proportion of gaze data points.							✓	✓		(1) Mean speed, (2) Min* speed, (3) One-degree steering reversal, (4) SD of lateral position, (5) Percent road centre.		✓			Merat (2014)	[124]
57	Decoupling of steering wheel.	✓									(1) Gaze RT, (2) Road fixation time, (3) Hands-on RT, (4) Max Acc, (5) Max steering wheel angle, (6) SD of lateral position.	✓	✓			Kerschbaum (2014)	[117]
58	(1) SuRT NDRT, (2) 2-back NDRT (3) No NDRT, (4) Obstacle and high traffic, (5) Obstacle and no traffic.			✓					✓		(1) TOT, (2) Max longitudinal Acc, (3) Min TTC (4) Amount of collisions, (5) Detection response task RT, (6) Criticality, (7) Complexity.	✓	✓	✓		Radlmayr (2014)	[73]
59	(1) 5.0 s TOT budget, (2) 7.0 s TOT budget.		✓								(1) Hands-on RT, (2) Road fixation time, (3) Gaze RT, (4) Side mirror gazing time, (5) Turn signal RT, (6) Max longitudinal Acc, (7) Max lateral Acc, (8) Max Acc, (9) Distribution of reaction types, (10) Trajectories.	✓	✓			Gold (2013)	[66]
60	(1) Manual driving, (2) Car following, (3) Cruise control, (4) Cruise control with active steering, (5) Broken down car, (6) Curve, (7) Exit.	✓						✓	✓		(1) Distribution of reaction types, (2) Percent road centre, (3) Braking behaviour, (4) Lane exceedance.	✓	✓			Kricher (2013)	[125]
61	(1) Person entering from the hard shoulder, (2) Compressor entering from the hard shoulder, (3) Person standing on the hard shoulder, (4) Compressor standing on the hard shoulder, (5) Driver in neighbouring lane swerving, (6) Narrowing down of lanes.								✓	✓	(1) Gaze RT, (2) Road fixation time, (3) Hands-on RT, (4) Min intervention RT, (5) Remaining action time, (6) Side mirror gazing time, (7) turn signal RT, (8) Max lateral Acc, (9) Max longitudinal Acc, (10) Max Acc, (11) Distribution of reaction types, (12) Monitoring state evaluation.	✓	✓			Gold (2013)	[92]
62	4 stages of criticality (no take-over, 0.5, 1.0, and 1.5 s headway).	✓	✓								(1) SAGAT* and, (2) SART* questionnaires, (3) Amount of collisions.			✓		Beukel (2013)	[67]
63	(1) Missing lane markings, (2) Reduction from 3 lanes to 2 lanes, (3) Intersection on the highway.								✓		(1) Driving errors, (2) trajectories, (3) Comfort of take-over.	✓	✓	✓		Dambock (2012)	[110]
64	(1) Two different TOR modalities (AV-V**, ANV-V**).	✓									(1) Mean speed, (2) Transition of control, (3) TOT, (4) Interface evaluation, (5) Driving performance.	✓	✓	✓		Toffetti (2009)	[56]

* TOT=Take-Over Time, TOR = Take-Over Request, TO = Take-Over, RT = Reaction Time, SD = Standard Deviation, TTC = Time To Collision, Max = Maximum, Acc = Acceleration, Min = Minimum, NDRT = Non-Driving-Related Task, SuRT = Surrogate Reference Task, SAGAT = Situation Awareness Global Assessment Technique Questionnaire, HRV: Heart Rate Variability, SART = Situation Awareness Rating Technique Questionnaire, TQT = conversational Twenty Questions Task [10], n-back task: Recall number n steps back, Arrow task= a manual-visual search for a "target" arrow. NDRT=Non-Related Driving Task. Simon game= Repeat pattern with colored buttons, Akinator tablet game=https://en.akinator.com/ [164], RSVP= Rapid Serial Visual Presentation [165].

** V = Visual, T = (vibro)Tactile, V-T=bimodal Visual-(vibro)Tactile, A = Auditory (not specified vocal or non-vocal), AV = Auditory-Vocal, A-V = bimodal Auditory-Visual, AV-V = bimodal Auditory (Vocal)-Visual, ANV = Auditory-NonVocal, ANV-V = biomodal Auditory (NonVocal)-Visual, A-T = bimodal Auditory-(vibro) Tactile, A-V-T=multimodal Auditory-Visual-(vibro)Tactile, ANV-T = bimodal Auditory(NonVocal)-(vibro)Tactile, AV-T=bimodal Auditory(Vocal)-(vibro)Tactile, AV-V-T=multimodal Auditory(Vocal)-Visual-(vibro)Tactile.

*** I1-I9: Independent variables. I1: Alert Type (TOR Modalities), I2: take-over time Budget, I3: Non-Driving-Related Task, I4: Training and System Knowledge, I5: Driver-Centric Factors, I6: Environmental Factors, I7: Level of driving automation, I8: Movement preceding collision, I9: Other road users

**** D1-D4: Dependent Variables. D1: Behavioural Measures, D2: Vehicular Measures, D3: Self-Reported Measures, D4: Physiological Measures.

5. Variables Extracted from on-Road Collision Reports

The California DMV website has been documenting collisions involving ADS-equipped vehicles since October 2014 [29], [166], [167]. We analysed these reports to identify variables and parameters that might influence a driver's reaction during collisions in ADS-equipped vehicles. This analysis can inform future experimental research scenarios, encouraging the design of more realistic experiments. Despite some shortcomings, analysing these reports is worthwhile as they are sourced from real-world situations. Also, no other datasets provide insights into general public collisions involving Level 3 (and higher) ADS-equipped vehicles.

DMV collision reports categorise the driving mode as either conventional or automated. Looking at the details of these reports, we can identify a third mode named transition mode. This mode applies to scenarios where a driver was actively engaged in driving at the time of a collision but was disengaged just moments before the incident (i.e., the vehicle switched from automated to conventional mode shortly before the collision). It should be noted that the DMV reports do not explicitly recognise a transition mode; we derived this classification from our in-depth analysis of 546 DMV reports until January 2023. We have assigned the collisions in the transition mode as our focus group. The importance of identifying collisions during this transition mode is supported by a report from NHTSA that examines real-world incidents involving Level 2 automation system-equipped vehicles. In this report, any collision occurring within 30 seconds of using the Level 2 system is also considered relevant [21].

From our analysis (comprehensive data can be found in the supplementary materials as well as an accompanying online Excel file [168]), 36.4% ADS-equipped vehicles were in the conventional mode at the time of the collision, 13.8% were in the transition mode, and 49.8% were in the automated mode. When an ADS-equipped vehicle is operated in the conventional mode, the driving responsibility is fully on the human driver, similar to driving a conventional vehicle. If a collision occurs while the ADS-equipped vehicle is in automated mode without alerting the driver beforehand, the automated system should be investigated. However, the driver's reaction plays a critical role in avoiding collisions when in transition mode.

Each collision report contains information about the car manufacturer, involved parties (vehicles/other road users), the injuries or damages, and the driving mode during the collision, among other details. This information was extracted and evaluated for all reports up until January 2023. The data can be divided into dependent and independent variables. Independent variables that influence the collision include environmental factors such as (1) weather conditions, (2) road lighting, and (3) road surface. Other independent variables include (4) other road users, (5) roadway layout, (6) movements of the ADS-equipped vehicle before the collision, and (7) movements of other road users preceding the collision. Dependent variables or measures extracted from the reports include (1) type of collision, (2) injuries, (3) damages to other involved parties, and (4) damage to ADS-equipped vehicles.

A. Independent variables from DMV reports

Figure 5 (a) shows the probability distribution of independent variables influencing collision rates across different driving modes, as derived from the DMV reports. Kullback-Leibler (KL) divergence was conducted to measure differences in DMV collision probability distributions across conventional, automated, and transition driving modes. Additionally, Chi-square tests were performed to assess the interactions between these driving modes and various independent variables. Table 2 presents the KL divergence and Chi-square test results for these independent variables.

1) Environmental Factors - Weather Condition: The first row in Fig. 5 shows the probability distribution of collisions across different weather conditions for each driving mode. For example, in our focus group, after excluding unknown conditions, 92% of collisions occurred in clear weather, 5% in cloudy conditions, and 3% during rain. Also, no collisions were reported in extreme conditions such as snow, fog, or wind. The low KL divergence, for weather conditions across the different driving modes indicate that weather is not a major differentiating factor in collision occurrence in DMV reports (see Table 2). Chi-square tests assess whether observed differences in distributions are statistically significant, with chi-square critical values determined by degrees of freedom (df) and significance levels (p) [169]. No significant differences in collision distributions across weather conditions were found ($df = 3$ for pairs of driving modes; $df = 6$, $\chi^2 = 11.97 < 12.59$ at significance level $p = 0.05$ for all three modes combined). However, since χ^2 value exceeds the critical threshold at significance level $p = 0.1$ ($df = 6$, $\chi^2 = 11.97 > 10.64$), the result may suggest marginal differences worth further investigation. This is supported by the higher KL divergence values between collisions in conventional mode and transition mode, as well as between automated mode and transition mode, as shown in Table 2, indicating that further exploration is needed. Moreover, given that the DMV reports involve test prototypes of ADS-equipped vehicles, it is possible that test drivers avoided conducting tests in rainy, cloudy, or foggy conditions. This avoidance could have influenced the collision distribution data, as the limited data points may have contributed to the observed lack of significant variation across different weather conditions.

2) Environmental Factors - Roadway Surface: The reports categorise roadway surfaces into four types: dry, wet, snowy-icy, and slippery. The second row in Fig. 5 displays the probability distribution of collisions across roadway surfaces for each driving mode, excluding unknown conditions. Notably, no collisions were reported on snowy-icy or slippery surfaces. Chi-square tests indicate no significant differences in collision distribution across roadway surfaces when comparing all three modes combined ($df = 2$, $\chi^2 = 0.10 < 5.99$ at significance level $p = 0.05$). However, the larger KL divergences involving transition mode KL(Auto||Trans) could merit further investigation to understand factors that may contribute to these variations.

3) Environmental Factors - Lighting: The probability distribution of collisions across different lighting conditions (daylight, dusk-dawn, and dark street) is shown in Fig. 5 and Table 2. A Chi-square test indicates a marginally statistically significant difference in the collision distributions across three modes of the conventional, transition, and automated ($\chi^2 = 10.43 > 9.48$, $df = 4$, at significance level $p = 0.05$). As shown in Table 2, the KL divergence value between automated and transition modes, KL(Auto||Trans)=0.58, is the highest among the comparisons, primarily due to the presence of dusk-dawn collisions in the automated mode (11 out of 229) and their absence in the transition mode. A pairwise Chi-square test ($df = 2$, $\chi^2 > 5.99$ at $p = 0.05$) further supports this difference, suggesting a higher collision rate under dusk-dawn conditions in automated mode compared to transition mode.

4) Other Road User: The DMV reports indicate collisions can involve vulnerable road users besides motor vehicles. We categorised other road users into three groups: (1) moving vehicles, (2) vulnerable users, including cyclists, pedestrians, scooter riders, and skateboarders, and (3) stationary vehicles or objects, such as parked vehicles, stopped vehicles in traffic, curbs, roundabouts, trees, traffic islands, and concrete posts. Figure 5 indicates that the probability distribution of collisions involving ADS-equipped vehicles in automated mode with moving vehicles is the highest compared to the other two modes (90% vs. 70% and 75%). Conversely, the probability distribution of collisions involving ADS-equipped vehicles in conventional mode, with stationary vehicle/object is the greatest (24% vs 9% and 5%). Lastly, the probability distribution of collisions involving ADS-equipped vehicles in transition mode with vulnerable users is the highest compared to the other modes (16% vs. 6% and 5%). The Chi-Square test indicates statistically significant differences in collision distributions across all three driving modes ($df = 4$, $\chi^2 = 62.63 > 9.48$ at significance level of $p = 0.05$), see Table 2. Significant differences were also observed among all driving mode pairs ($df = 2$, $p < 0.05$). These results suggest that collision distributions are significantly impacted by the presence and actions of other road users and highlight the need for future research.

5) Movement Preceding Collision - Roadway Layout: The DMV reports list several road shapes, including construction and repair zones, reduced roadway width, obstructions, and no unusual conditions. The low KL divergence values across the different driving modes (see Table 2) suggest that roadway conditions are not a major differentiating factor in collision occurrence in DMV reports. In addition, using Chi-Square tests, it was shown that there are no significant differences in the distribution of collisions across roadway layouts when comparing any pair of driving modes and all three driving modes ($df = 2$, $p > 0.05$ and $df = 4$, $p > 0.05$).

6) Movement Preceding Collision - ADS-Equipped Vehicle: Different types of ADS-equipped vehicle movement that precede a collision include proceeding straight, stopping in traffic, and performing other manoeuvres such as lane changes, slowing down, or coming to a stop, etc. The Chi-Square test indicates statistically significant differences in collision distributions across all three driving modes ($\chi^2 = 55.80$, $df = 4$, $p < 0.05$). Additionally, significant differences were observed between pairs of driving modes ($df = 2$, $p < 0.05$). In transition mode (the focus group), the probability of collisions involving ADS-equipped vehicles while moving straight is

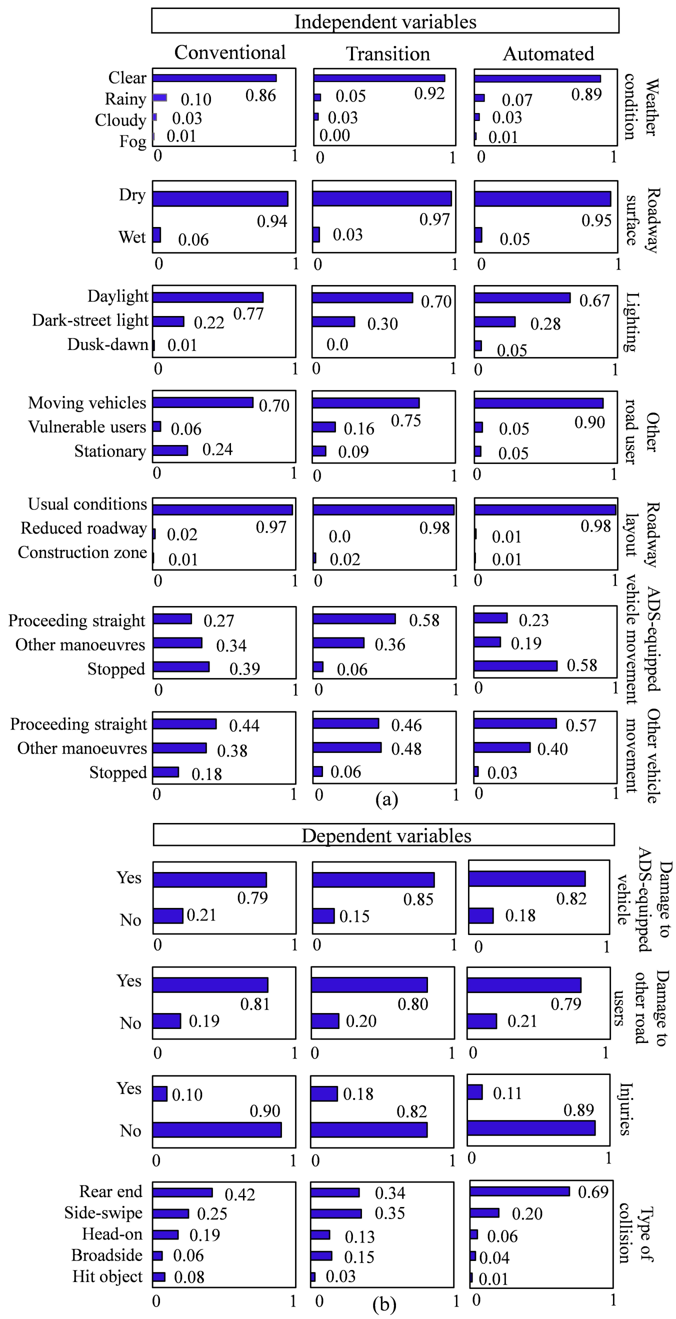

Fig. 5. The probability distribution of independent and dependent variables across three states of the ADS-equipped vehicle: conventional mode, transition mode, and automated mode. (a) The DMV reports include several independent variables: (1) weather condition, (2) roadway surface, (3) lighting, (4) road condition, (5) interactions with other road users/components, (6) movement of the ADS-equipped vehicle preceding the collision, and (7) movement of other road users preceding the collision. (b) The DMV reports include several dependent variables, including: (1) damage to ADS-equipped vehicles, (2) damage to other road users, (3) injuries, and (4) type of collision.

TABLE 2
STATISTICAL ANALYSIS OF DRIVING MODES: KL DIVERGENCE AND CHI-SQUARE TEST RESULTS ACROSS INDEPENDENT AND DEPENDENT VARIABLES.

	Conv||Trans	Trans||Conv	Conv||Auto	Auto||Conv	Trans||Auto	Auto||Trans	Chi-square critical value (df)*	Chi-square value	Significant difference
Independent variables	KL Divergence						Chi-square test		
Weather	0.1383	0.0295	0.0063	0.0059	0.0159	0.1472	12.59 (6)	11.97	×
Roadway surface	0.0074	0.0062	0.00034	0.00033	0.0034	0.0044	5.99 (2)	0.10	×
Lighting	0.1302	0.0270	0.0371	0.0508	0.0527	0.5815	9.48 (4)	10.43	√
Roadway condition	0.1965	0.0238	0.0033	0.0027	0.0183	0.0990	9.48 (4)	2.49	×
Other road users	0.1303	0.1265	0.6289	0.1116	0.2890	0.0103	9.48 (4)	62.63	√
ADS-equipped vehicle movement	0.4628	0.3363	0.0887	0.0842	0.5946	0.9108	9.48 (4)	55.80	√
other road user movement	0.0803	0.0616	0.1901	0.1152	0.0171	0.0330	9.48 (4)	29.51	√
Dependent variables									
Damage to ADS-equipped vehicle	0.0094	0.0128	0.0062	0.0044	0.0017	0.0013	5.99 (2)	0.73	×
Damage to other road user	0.0057	0.0054	0.0121	0.0107	0.0058	0.0053	5.99 (2)	0.09	×
Injuries	0.0250	0.0295	0.0005	0.0005	0.0215	0.0187	5.99 (2)	4.50	×
Type of collision	0.0902	0.0866	0.2536	0.1869	0.2870	0.2662	15.50 (8)	54.99	√

* Chi-square critical values are referenced from [169]. All critical values correspond to a significance level of $p = 0.05$. Degrees of freedom (df) are calculated as $df = (r-1)\times(c-1)$, where r is the number of driving modes (e.g. three driving modes of conventional, transition, and automated) and c is the categories per variable (e.g., four categories for weather conditions, as shown in Fig. 5).

higher compared to the other two modes (58% vs. 27% and 23%). Furthermore, the likelihood of collisions during other manoeuvres, such as lane changes or slowing down, is also the highest in transition mode (36% vs. 34% and 19%). In automated mode, however, collisions involving stationary ADS-equipped vehicles have the highest probability (6% vs. 39% and 58%).

7) Movement Preceding Collision - Other Road User: For the movement of other road users preceding collisions, the Chi-Square test reveals statistically significant differences in collision distributions across all three driving modes ($\chi^2 = 29.51$, $df = 4$, $p < 0.05$). Significant differences were also observed in pairwise driving modes comparisons ($df = 2, p < 0.05$). The probability distribution of collisions involving ADS-equipped vehicles in automated mode, while the other road user is proceeding straight before the collision, is the highest compared to the other two modes (57% vs. 44% and 46%). The probability of collisions involving ADS-equipped vehicles in transition mode is higher when the other road users are performing other manoeuvres, compared to the other two modes (48% vs. 38% and 40%). The probability of collisions involving ADS-equipped vehicles in conventional mode is higher when the other road user is stopped, compared to the other two modes. The significant differences in the Chi-square test results suggest that driving modes interact differently with the various movements of other road users.

B. Dependent variables

A summary of the dependent variables extracted from reports is shown in Fig. 5 (b) and Table 2. This includes both the type and extent of damage to the vehicles, as well as any injuries that occurred in the collisions.

- *Damage to ADS-equipped vehicles*: The ADS-equipped vehicles were damaged in 85% of collisions during the transition mode, 79% in the conventional mode, and 82% in the automated mode. The Chi-Square test reveals no statistically significant differences in damage to the ADS-equipped vehicle across the three driving modes ($\chi^2 = 0.73$, $df = 2$, $p > 0.05$), see Table 2.
- *Damage to other road users*: Damage to other road users occurred in 80% of collisions when the ADS-equipped vehicle was in transition mode, 81% in conventional mode, and 79% in automated mode. The Chi-Square test reveals no statistically significant differences in damage to ADS-equipped vehicles across all three driving modes ($\chi^2 = 0.09$, $df = 2$, $p > 0.05$), see Table 2.
- *Injuries*: Most collisions did not result in injuries. The Transition mode exhibited a slightly higher proportion of injury crashes (18%) compared to the Conventional (10%) and Automated (11%) modes. However, both the KL divergence values and the Chi-square test indicate that these differences are not statistically significant (see Fig. 5(b) and Table 2).
- *Type of collision*: The reports describe various types of collisions, including rear-end, side-swipe, head-on, broadside, hitting an object, and others. As shown in Fig. 5 (b), the most common type of collision is the rear end. Among these, vehicles operating in automated mode exhibit the highest proportion of rear-end collisions, at 69%. In the focus group, where the vehicle is in transition mode, side-swipes are most common at 35%, closely followed by rear-end collisions at 34%. Other less frequent types of collisions include head-on, broadside, and hitting objects. The chi-square test revealed a statistically significant difference between collision type and driving mode ($\chi^2 = 54.99$, $df = 8$, $p < 0.05$), indicating that the distribution of collision types varies meaningfully across conventional, transition, and automated driving modes (see Table 2).

6. Discussion: Synergies and shortcomings in literature and DMV reports

To lay a foundation for further research, this paper highlights two methods for identifying the independent variables likely to influence driver′s reaction during transitions, as well as the dependent variables that can be used for assessment. First, both sets of variables have been extracted from research involving reaction of the driver to take-over requests during the transition of control between automated and manual driving. Second, on-road collisions involving test vehicles equipped with ADS were analysed to identify possible variables that can impact reaction in a way that jeopardises the safety of drivers and other road users. The dependent and independent variables derived from the two methods are summarised and categorised in Fig. 6. We discuss the synergies and shortcomings of these variables extracted from the reviewed papers and DMV reports in Subsections 6-A and 6-B, respectively. These insights, combined with potential variable combinations, can guide the design of scenarios and experiments assessing driver reactions in ADS-equipped vehicles.

A. Synergies and shortcomings of independent variables in literature and DMV reports

Figure 6 (a) and (c) provide a summary of the independent variables extracted from Sections 4-A and 5-A. Independent variables identified in the literature include (1) Alert type, (2) Take-over time budget, (3) Non-driving-related tasks, (4) Training and system knowledge, (5) Driver-centric factors, (6) Environmental factors, (7) Driving automation level, (8) Movement preceding collision, and (9) Other road users. DMV reports highlight three key variables: (1) Environmental factors (e.g., weather, road surface, lighting), (2) Other road users, and (3) Movement preceding collision (ADS vehicle movement, other road user movement, and roadway layout). These key variables are highlighted for further investigation to enhance understanding of safety considerations and user reactions to vehicles with automated driving systems:

1) Alert type (TOR modalities): The alert type in Section 4 includes visual, auditory, haptic feedback, and all bimodal and multimodal combinations of these alerts. As discussed in Section 4, many studies have investigated different alert types as part of the take-over process, e.g. research on various auditory and visual alerts is well-established. However, studies focusing on vibrotactile haptic feedback alerts are limited. There is also a lack of research on haptic feedback systems that rely on non-vibrotactile methods. Additionally, multimodal alerts that contain haptic feedback, such as multimodal audio-visual-non-vibrotactile alerts and multimodal audio-visual-vibrotactile alerts, are rarely studied [88]. These areas could be further explored (see Fig. 3, Table B.1, and Fig. 6). DMV reports currently lack details on alert types (if present), and incorporating these details in future collision reports would be beneficial.

2) Take-over time budget: As discussed in Section 4, the take-over time budget has been extensively studied in driving simulator research. However, DMV collision reports do not provide this information for public audiences (as mentioned in Section 5), which is valuable to be included. Driving simulator environments differ from on-road situations. Hence, the time between taking over and a collision, or between spotting a scene and a collision, might differ in on-road collisions compared to driving simulator studies.

3) Non-driving-related task: Non-driving-related tasks have been used as an independent variable in many of the reviewed papers in Section 4. These tasks can include cognitive, motoric, or visual activities for instance. Research has shown that different types of non-driving-related tasks have different influences on take-over performance. For instance, cognitive and motoric non-driving-related tasks have been found to differentially impact cognitive-demanding and Well-practised take-over situations [57]. The reviewed papers indicate that most studies on non-driving-related tasks are conducted in driving simulators. However, there's a need to explore how these tasks affect take-over performance in real-world scenarios, especially since current DMV collision reports don't capture details about drivers' engagement in non-driving-related tasks. In driving simulator studies, non-driving-related tasks are typically assigned to participants, whereas in real-world scenarios, drivers might initiate take-over requests [97], and further research is needed to explore the effects of self-initiated take-over requests on take-over performance.

4) Training and system knowledge: There is evidence in the literature that different types of training influence take-over performance. Hence, further examination of the various types and durations of training would be beneficial. Moreover, considering that the drivers mentioned in the DMV reports are trained, details regarding their training level might be valuable additions to the reports. Existing literature has shown that different training levels affect the reaction of the driver. Hence, relying solely on trained safety drivers might not accurately represent the driving behaviours of the general public, introducing a limitation to DMV collision reports. According to Endsley's theory of situational awareness (SA), successful decision-making in dynamic systems depends on a driver′s ability to progress through three levels of SA: perceiving critical information (Level 1 SA), comprehending its significance (Level 2 SA), and projecting future states (Level 3 SA) [170]. For ADS-equipped vehicles, the driver′s perception and knowledge of key system capabilities and limitations (Level 1 SA) form the foundation for higher-order comprehension and decision-making. If drivers do not have enough data/knowledge about the boundary and limitations of the 'level of driving automation', they may not be able to perceive the situation, leading to inappropriate decisions or reactions. A real-world example of this scenario is the fatal collision that happened in April 2021 [171], [172], in which a vehicle with a Level 2 driving automation system was driverless at the time of the collision. The absence of a driver in the seat suggests a lack of SA Level 1; the driver likely did not understand the system's boundaries and limitations, resulting in the unsafe and illegitimate decision to vacate the seat while the vehicle was in motion at high speed, ultimately causing the fatal accident. Such incidents underscore the need to assess drivers′ knowledge of system limitations and boundaries and to include this information in DMV reports.

5) Driver-centric factors: Research in Section 4 shows that a driver′s emotional state affects take-over performance. Positive emotional valence improves take-over time and quality, while high arousal has no significant impact [80], [105]. Driver reaction time is also influenced by age and driving history, especially when comparing novice and experienced drivers [71], [84–86].
However, DMV reports primarily focus on vehicle performance with trained drivers and do not consider human-centric factors such as emotional state, fatigue, and trust in automation. Trained drivers may perform better due to their familiarity with vehicle dynamics, which means the results may not reflect how novice or less-experienced drivers interact with automated systems. Further research should explore these human factors, particularly how emotional state, fatigue, and trust affect take-over performance in real-world conditions.

6) Environmental factors: Environmental conditions described in the DMV reports varied from clear to inclement, including cloud, rain, snow, fog, and wind. Although there is a substantial body of research on the effects of environmental conditions on advanced driver assistance systems [173–180], limited studies have investigated a driver's reaction in response to a combination of roadway lighting, roadway surface, and weather conditions during the transition of control. Heo et al. [16] found that adverse environmental conditions, such as snow, rain, fog, and nighttime driving, significantly impact driver take-over performance by increasing response time, lane change duration, and mental workload. They also demonstrated that specific alert systems could effectively mitigate these effects. In contrast, our DMV reports′ statistical analysis suggests that weather and roadway surface conditions are not major differentiators in collision occurrences during ADS testing. This difference may be due to the controlled nature of DMV test scenarios, where adverse conditions are likely underrepresented. These contrasting observations highlight the need for further research to explore the combined effects of environmental factors on driver behaviour during take-over events, particularly under diverse and realistic conditions.

7) Level of driving automation: As discussed in Section 4, most studies in driving simulator environments primarily examine the reaction of the driver during the transition from full automation to manual driving. Usually, the specific level of full automation is not clear (e.g., whether it is Level 3 or Level 4 automation). Different levels of autonomy can influence drivers' responses to take-over requests. As driving becomes less demanding with higher levels of automation, drivers may shift their focus more toward non-driving-related tasks. This shift can be explained through the Multiple Resource Theory (MRT), which suggests that when the cognitive load of driving decreases, drivers are likely to redirect their attention to other tasks, potentially impairing performance if a manual take-over is required suddenly [30], [108]. Investigating and comparing the driver′s reaction in the transition of control between different levels of autonomy can be the subject of future research. For instance, an independent variable can be the transition of control between Level 3 and Level 0 versus the transition of control between Level 4 and Level 0. A positive aspect of some DMV reports (some Waymo LLC reports) from 2021 is the explicit specification of the ADS system's autonomy level. In addition, it is important that other companies incorporate this level of detail when preparing their DMV reports.

8) Movement preceding collision: There is a variety of movements preceding collision, as observed in on-road collision reports and variables extracted from the reviewed papers (see Fig. 5 (a) and (b): Movement preceding collision/critical situation). In both research and collision reports, similar movements are considered preceding a collision or critical situation, such as lane changes, exits, and U-turns. However, research can still be enriched by considering on-road scenarios. According to Fig. 5 (a), the most common movement of an ADS-equipped vehicle before a collision in transition mode is proceeding straight, followed by changing lanes and stopping or slowing down. While an ADS-equipped vehicle is in transition mode, the two most common pre-collision movements for other vehicles are proceeding straight ahead and changing lanes. These patterns provide insights for future driving simulator study designs.

9) Other road users: According to the DMV reports, collisions may involve not only other motor vehicles, but also bicycles, scooters, motorbikes, and pedestrians. Although there are many studies about detecting other road users by using advanced driver assistance systems [181–188], there is a research gap concerning the drivers′ reactions when facing vulnerable road users such as pedestrians, bicycles, and scooters during transition of control.

B. Synergies and shortcomings of dependent variables

Figure 6 provides an overview of all measurable metrics. It is based on dependent variables extracted from reviewed papers in Subsection 4-B and those reported in on-road collisions from Subsection 5-B. As stated in Section 4, a total of 74 dependent variables or measurable metrics were extracted from reviewed papers in the driving simulator environment. These dependent variables are split into two categories: self-reported measures and objective measures. Self-reported measures involve participants expressing their own attitudes, beliefs, and behaviours via a questionnaire. On the other hand, objective measures are consistent variables that remain unchanged irrespective of the person performing the measurement or the tool employed for measurement. In Fig. 6, the objective measures are further divided into three subcategories:

- Behavioural measures
- Vehicular measures
- Physiological measures

Technological progress, especially the arrival of behavioural and physiological sensors, allows for new ways to measure driver reactions. Most of the behavioural measures in the reviewed papers are time-based, possibly due to ease of use. These measurements include various reaction times, such as hands-on, steer initiate, steer turn, pedal, turn signal, and lane change, among others. Other research relies on measuring gaze behaviour using an eye tracker or RGB camera [57], [61], [66], [72], [83], [92], [111], [115–117], [122], [123], [189], see Table C.1 and Fig. 6. In section 3.2.1, we delved into extensive research on the correlation between EEG and driver reactions. However, it's worth highlighting that various other psychological sensors can also contribute significantly to the evaluation of driver responses. These sensors, encompassing Electrocardiography (ECG), Electrooculography (EOG), Electrodermal Activity (EDA), Magnetoencephalography (MEG), and Functional Near-Infrared Spectroscopy (fNIRS) form a robust toolkit for assessing a driver's mental state. This inclusive set of sensors allows for the evaluation of factors such as fatigue, workload, and sleepiness, as evidenced by prior studies [190–199]. Furthermore, these sensors can be employed to assess driver reactions in ADS-equipped vehicles, as depicted in Fig. 6. Translating the measures from a simulated driving environment to the real world, and vice versa, is a challenge. In real-world scenarios, based on data made public by the DMV (see Subsection 5-B), the measurable variables are:

- Type of collisions
- Injuries
- Damage to ADS-equipped vehicle
- Damage to the other road users

It is obvious that actual physical damages and injuries cannot be replicated within a driving simulator environment. However, potential damages and injuries in a virtual driving simulator environment can be modelled and estimated. For instance, proxy variables such as a vehicle's momentum during a collision could serve as damage estimators. This allows us to differentiate between drivers who are unaware of what is going on, from those who made efforts and succeeded in avoiding collision and injuries. This is an area for future research.

C. Priority of variables in literature review studies

Some meta-analyses have discussed the priority of different variables and their effectiveness in the transition of control. For example, the meta-analysis by Weaver et al. focused on three independent variables: time budget, non-driving-related tasks, and information support during the take-over, assessing their impact on two dependent variables: take-over timing and quality measures. They indicated that a shorter time budget led to faster take-over timing and poorer quality. Engaging in non-driving-related tasks also made it harder for drivers to take over effectively [41]. Soares et al. meta-analysis found that simpler experiments without secondary tasks and conducted in low-fidelity simulators are associated with quicker take-over times and lower crash rates. Many studies used convenience samples with limited demographic variability, and virtual environments may reduce perceived crash risk, leading to slower reactions compared to real-world driving [48]. McDonald et al. revealed that drivers respond similarly to manual emergencies and automated take-overs, though with a delay, suggesting that existing braking and steering models may be applicable to automated take-overs. Factors such as time budget, repeated exposure, silent failures, and handheld secondary tasks strongly influence take-over time, while post-take-over control is impacted by these factors as well as fatigue, trust in automation, alcohol impairment, and the driving environment [47]. Zhang et al. conducted a meta-analysis of determinants of take-over time in automated driving systems at Level 2 or higher. They found that shorter mean take-over times were associated with higher urgency situations, the absence of handheld devices, not performing visual non-driving tasks, previous experience with take-over scenarios, and receiving auditory or vibrotactile take-over requests. Interestingly, no consistent effect of age on take-over time was observed across the studies [43]. The paper by Hu et al. conducts a meta-analysis to examine the impact of non-driving-related tasks on take-over time during the transition of control. They categorised non-driving-related tasks into visual, auditory, motoric, and mental dimensions and found that both visual-mental-motoric and visual-mental tasks significantly increase TOT. The analysis reveals that older drivers and those with more experience demonstrate longer TOT when confronted with Non-driving-related tasks, along with gender-specific differences in TOT based on task modality [34]. Through a systematic review and meta-analysis, Hungund et al. found a significant increase in take-over times while engaging in non-driving-related tasks and driving with automation active. Studies also discuss a change in drivers' visual attention, with more focus given to non-driving-related tasks as compared to the front roadway [31].

D. Distribution of variables in take-over performance studies

A total of 64 studies have been reviewed in this paper, as summarised in Table 1. Looking at the distribution of variables in take-over performance studies shown in Table 3, it can be seen that the most frequently studied variables include non-driving-related tasks (I3), alert type (I1), and take-over time budget (I2). Non-driving-related tasks were examined in 25 out of 64 studies (39%), alert types in 24 studies (37.5%), and time budget in 17 studies (26.5%).

In contrast, variables such as training and system knowledge (I4), environmental factors (I6), and other road users (I9) were studied less frequently. For example, only 4 out of 64 studies (6.25%) included training and system knowledge, environmental factors appeared in just 2 studies (3.1%), and other road users were also included in only 2 studies (3.1%). Other variables include driver-centric factors (I5) in 11 studies (17.1%), level of driving automation (I7) in 12 studies (18.75%), and movement preceding collision (I8) in 17 studies.

TABLE 3
DISTRIBUTION OF INDEPENDENT AND DEPENDENT VARIABLES ACROSS 64 STUDIES

	Independent Variables		
	Variable	**No of studies**	**Frequency***
I1	Alert type (TOR modalities)	24	37.5%
I2	Take-over time budget	17	26.5%
I3	Non-driving-related tasks	25	39.0%
I4	Training and system knowledge	4	6.25%
I5	Driver-centric factors	11	17.1%
I6	Environmental factors	2	3.1%
I7	Level of driving automation	12	18.75%
I8	Movement preceding collision	17	26.5%
I9	Other road users	2	3.1%
	Dependent Variables		
	Variable	**No of Studies**	**Frequency****
D1	Behavioural measures	58	90.6%
D2	Vehicular measures	46	71.8%
D3	Self-reported measures	32	50.0%
D4	Physiological measures	7	10.9%

* and ** Totals do not sum to 100% as individual studies often examined more than one independent and more than one dependent variable. Frequencies are based on a total of 64 studies.

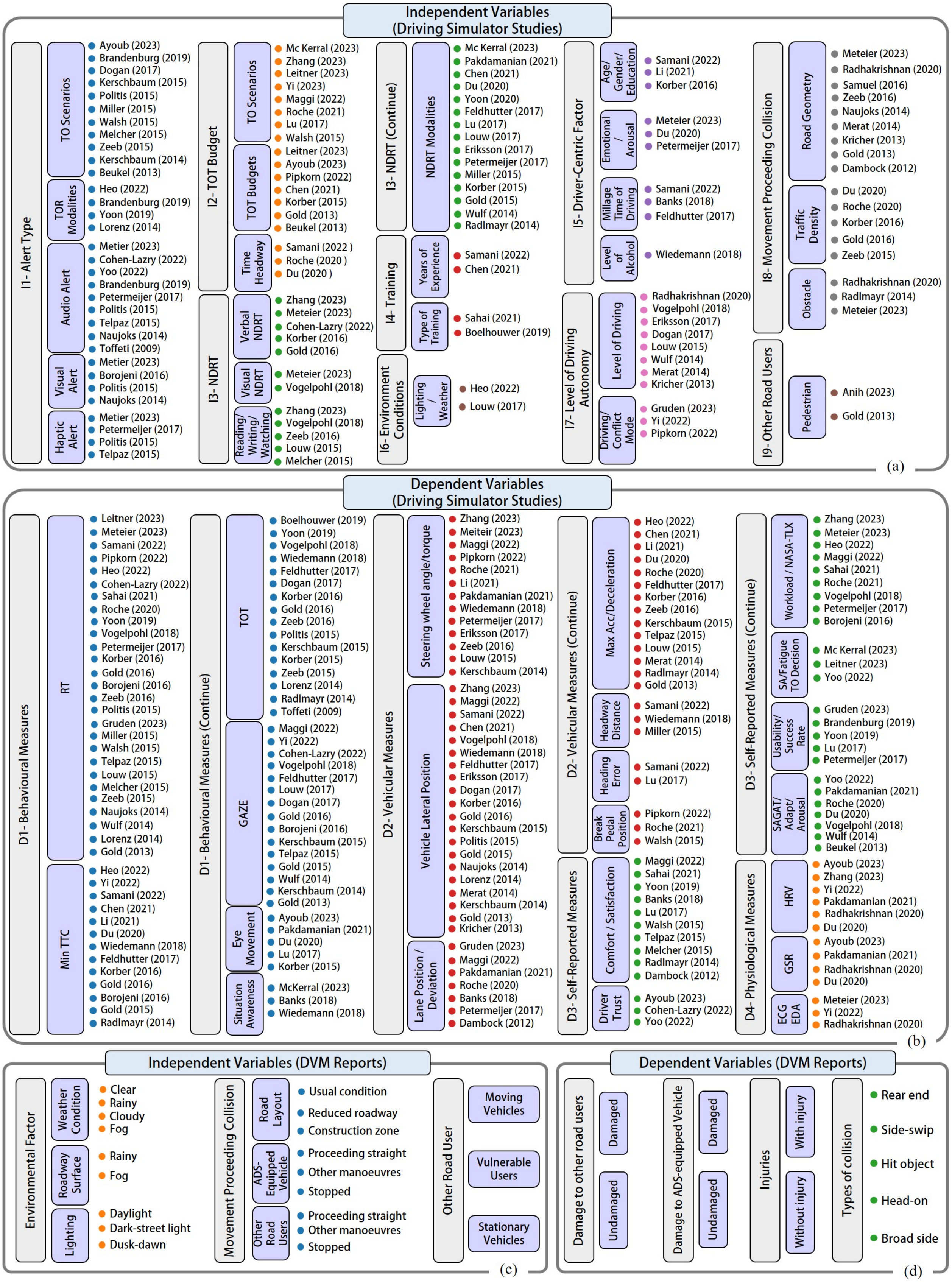

Fig. 6. (a) Independent variables extracted from driving simulator studies (Section 4), (b) Dependent variables extracted from driving simulator studies, (c) Independent variables extracted from on-road collision DMV reports (Section 5), (d) Dependent variables extracted from on-road collision DMV reports.

Regarding dependent variables, the analysis reveals that behavioural measures were the most commonly studied, appearing in 58 out of 64 studies (90.6%). Vehicular measures were studied in 46 studies (71.8%), self-reported measures in 32 studies (50.0%), while physiological measures were the least frequently studied, appearing in just 7 studies (10.9%). Please note that the totals do not sum to 100%, as individual research often studies multiple independent and dependent variables.

E. Additional variables from on-road collisions

At fault in an accident refers to the party who is judged to be legally responsible for the occurrence of the accident [200]. The DMV reports are self-reported and suffer from inconsistencies. In addition, there is a lack of data from police reports. Due to these limitations, the actual cause of the collisions is not explicitly specified. However, for our analysis, we reviewed the report narratives and classified DMV collisions into two categories: collisions where the ADS-equipped vehicles were at fault, and collisions where other road users or components were responsible.

As shown in Fig. D.1, ADS-equipped vehicles were at fault in 18.7% of all collisions. Among these, 62.7% were in the conventional mode, 21.6% were in the transition mode, and 15.7% were in the automated mode. Other road users were at fault in the remaining 81.3% of collisions, with 30.4% of the ADS-equipped vehicles in the conventional mode, 11.9% in the transition mode, and 57.7% in the automated mode. In collisions where the ADS-equipped vehicle was in the transition mode and at fault (accounting for 21.6% as shown in Fig. D.1), the reaction of drivers in the transition of control can be crucial in determining strategies to prevent future collisions. In addition, detailed dependent and independent variables extracted from reports considering instances where ADS-equipped vehicles were at fault specifically those in transition mode, are presented in Fig. E.1.

Besides the previously mentioned ambiguous variable (i.e., determining the potential causer), the DMV collision reports have several other debated limitations. For instance:

- The ADS-equipped vehicles in the reports are research prototypes.
- The drivers are specially trained safety drivers, who are not representative of the broader driving public.
- Most tests involve two individuals per vehicle, with a test operator in the passenger seat monitoring the automated driving system's performance.
- There is potential for drivers to intervene in critical situations to reduce collision risks.
- Since the vehicles being tested are research prototypes, their technology and user interfaces may not meet the standards expected of production systems for public use [201], [202].

Despite these limitations, DMV reports have been used in several studies [201–205]. The DMV has been publishing two types of reports, and researchers utilised both types: those documenting collisions [29] and those detailing the reasons for automated driving system disengagements [206]. Disengagements are not always associated with accidents (only one out of every 178 disengagements results in a collision) [207]. Zhang et al. [201] used machine-learning techniques to analyse the disengagement reports, revealing that over 80% of disengagements were initiated by test drivers. Also, 75% were caused by errors in perception, localisation, mapping, and planning. Favaro et al. [204] focused on studying reported contributory factors and probable causes of disengagements, as well as estimating disengagement frequencies and average mileage driven prior to disengagement. They emphasised the importance of studying disengagements as they can potentially lead to accidents. Banerjee et al. [205] also studied disengagement and accident reports to understand the causes, dynamics, and impacts of such failures. They reported that in terms of accident rates, vehicles with driving automation systems, were 15 to 4000 times more likely to be involved in accidents per mile driven compared to human-driven vehicles. Notably, 64% of disengagements were attributed to issues within the machine learning system or untimely decisions made by it. Aziz et al. [208] proposed a data-centric framework to identify human-critical testing zones. They employed both machine-learning and econometric models using crash data, finding a high correlation between rear-end collisions and injury occurrences. The analysis of Dadvar et al. [209] indicated that rear-end collisions and sideswipes were the most frequent accident types, and the majority happened in a relatively small area. Factors like road surface, other vehicle movements, intersection/control type, and crash time were identified as contributing elements. Das et al. [210] identified six types of collisions in his study. These were linked to turning manoeuvres, multi-vehicle incidents, low-light conditions with streetlights present, sideswipes, and rear-end collisions.

F. Future work

The foundation for designing a research scenario in the field of assessing the reactions of ADS users during transitions is based on defining both dependent and independent variables and understanding how to measure them. As extensively discussed in this paper, any combination of the aforementioned variables can be a new research scenario. As an example, a novel research scenario derived from this paper might involve modifying the road lighting, then measuring gaze reaction time with an eye tracker, or assessing brain activity using an EEG device. Other research gaps extracted from reviewed papers and DMV reports are summarised as follows:

- *Who initiates the take-over request:* In almost every study explored in Section 4, the hands-on request was issued by the ADS to the driver, and then the driver's feedback was reviewed. In real-world situations, drivers may request to go hands-on by their own choice, and such instances should be further investigated. At present, the hands-on request from the driver is only explored in research by Banks and Stanton [97] and Erikson and Stanton [51]. However, Eriksson et al. [51] describe that post-handover (manual) driving performance improves when the handover is user-paced rather than system-paced, indicating that letting the driver choose the ideal point for take-over might be preferable. Additionally, Gershon et al. found that in real-world situations, drivers typically initiated take-over requests to perform tasks beyond the automation's capabilities or to meet personal preferences, rather than to address immediate safety concerns [211]. The distinction between system- and driver-initiated take-overs highlights questions about how transition dynamics influence driver performance and overall safety. More research is needed to better understand their influence on the system, driver behaviour, and safety outcomes. The implications and outcomes of driver-initiated take-over tasks require more consideration in future studies.

- *Real world experiments:* Although there are many real-world studies on the functionality of the ADS-equipped vehicles [212–215], research focusing on real-world reactions of automation system users is limited to a few numbers of studies, for example, a study conducted in a Tesla Model SP90 (Level 2 of driving automation system) showing that drivers may struggle with their monitoring responsibilities, occasionally displaying signs of over-trust on the system [97]. Another real-world study incorporates an ADS-equipped vehicle with adaptive cruise control (Level 1 of the driving automation system). They identified that visual behaviour, reaction speed, and adaptive cruise control experience significantly impact take-over times [216]. Moreover, some researchers, such as Dikmen et al. [217], utilised self-reported measures to investigate user experiences with ADS-equipped vehicles. They emphasise the need for a better understanding of automation limitations and the importance of user education about the complexities of automated driving. The limited research conducted to date highlights the need for further studies focusing on real-world user interactions with automated driving systems.
- *Physiological measures to assess driver's reaction:* Physiological measures have significant potential for assessing driver states during transitions of control in ADS-equipped vehicles. They provide quantitative data on situational awareness, stress, workload, and emotional arousal. However, a notable gap exists in the comprehensive application of these measures in take-over scenarios. For instance, while studies like Pakdamanian et al. have used EEG to evaluate drivers' responses to alerts during take-overs, these findings involved only a limited number of participants [128]. Similarly, Zhou et al. demonstrated a correlation between EEG signals and reaction times, showing that EEG could act as a proxy for vigilance, but the research has yet to confirm its robustness in practical driving contexts [140]. Furthermore, research has shown that ECG, HRV, GSR, EDA, SCR, and RESP can predict take-over quality, as seen in studies by Ayoub et al. [137], Meteier et al. [134–136], Pakdamaniana et al. [128], Radhakrishnan [109] and Du et al. [138]. However, these studies mostly focus on controlled environments, with limited application to real-world scenarios. While some studies suggest the value of combining multiple physiological measures, such as HRV, GSR, and EEG, there is a gap in research integrating these measures to assess driver states during transitions in ADS-equipped vehicles. Building on this foundation, an additional critical gap lies in leveraging physiological measures for assessing drivers' states (e.g. situational awareness) during control transition. For example, Kästle et al. [218] proposed a data-driven methodology to identify EEG signatures associated with situation awareness based on an assessment in the Psychology Experiment Building Library (PEBL) that closely follows Endsley's definition of situational awareness [219–222]. Similarly, Krol et al. [223] suggested a methodology that uses EEG signals to classify situational awareness levels, tested using a data set from a PEBL-based situational awareness evaluation. They identified specific frequency bands linked to awareness levels and related them to brain regions associated with pattern recognition and visuo-spatial abilities. The methodologies from both [218], [223] can be readily used to assess the situational awareness of ADS-equipped vehicle drivers. However, the effectiveness of these methods, particularly during take-over requests, remains to be determined.

G. Scenario to Inform Future Research

Selecting variables: Table 4 extracted from Table 1 summarises the number of combinations of variables studied in the 64 research papers (see Section 4). For instance, studies with other road users (I9), training and system knowledge (I4), or environmental factors (I6) as independent variables have the lowest number of studies and dependent variables such as physiological measures (D4) have the lowest number of studies. Combinations of independent and dependent variables with lower representation might highlight a gap in research and warrant further investigation. The statistical analysis of DMV reports in Section 5 (see Table 2) demonstrated that certain independent variables, such as other road users or type of ADS-equipped vehicle movement, result in significant differences in collision distributions across all three driving modes. Therefore, variable combinations with fewer studies in Table 4, but significant differences in real-world collision reports, require further investigation. In the following a case study is mentioned to demonstrate how the findings of this paper can be used to design a scenario.

Scenario to inform future research: Based on the information presented in Table 4 and Section 4, studies involving vulnerable road users (including cyclists, pedestrians, scooter

TABLE 4
INTERACTIONS BETWEEN INDEPENDENT AND DEPENDENT VARIABLES

Measures	I1	I2	I3	I4	I5	I6	I7	I8	I9	Total
D1	21	15	22	3	12	2	10	15	2	102
D2	16	10	15	2	12	1	10	11	2	79
D3	15	11	12	1	5	1	4	4	0	53
D4	2	3	3	0	1	0	1	4	0	14
Total	54	39	52	6	30	4	25	34	4	248

* I1: Alert type, I2: Take-over time budget, I3: Non-driving-related task, I4: Training and system knowledge, I5: Driver-centric factors, I6: Environmental factors, I7: Level of driving automation, I8: Movement preceding collision, I9: Other road users, D1: Behavioural measures, D2: Vehicular measures, D3: Self-reported measures, D4: Physiological measures.

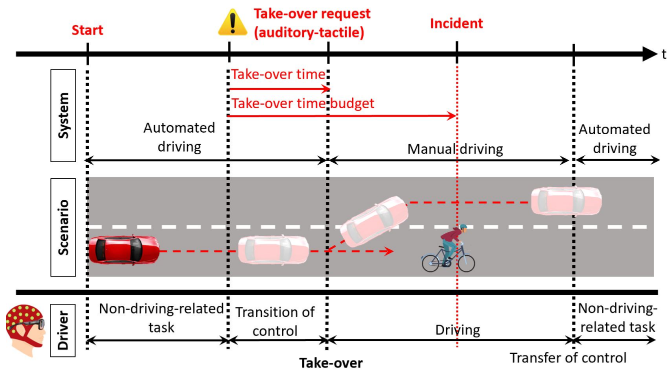

Fig. 7. A schematic illustration of a takeover scenario used for an example study, showing: 1) system status; 2) scenario progression; and 3) driver activity over time. The ego vehicle (in red) operates in automated mode until an auditory-tactile take-over request is issued. The driver transitions from a non-driving-related task to manual control during the takeover period. The takeover time and the available takeover time budget are marked. Following the TOR, a cyclist suddenly appears in the lane, requiring the driver to take control and respond to the incident. After the event, control is returned to the automated system and the driver resumes the non-driving-related task (inspired by the experimental design in Pakdamanian et al [158]).

riders, and skateboarders) as independent variables are limited. Table 4 further indicates that none of the 64 reviewed studies used a combination of self-reported and physiological measures as dependent variables with other road users as independent variable. Hence, selecting this combination could address an underexplored area and provide a valuable direction for future research. On the other hand, statistical analysis of DMV reports indicated significant differences in collision distribution involving vulnerable road users versus moving vehicles during the transition of control.
Therefore, as a scenario example, other road users are considered as an independent variable and a study is designed to assess drivers' Situational Awareness (SA) by comparing drivers' responses to a cyclist suddenly appearing on the road versus a motor vehicle suddenly appearing on the road, both using an urgent auditory-tactile take-over alert (see Fig. 7).
To assess the driver's SA, dependent variables are drawn from four categories— self-reported, vehicular, behavioural, and physiological measures — each represented in Fig. 6. Reviewing dependent variables across the studies presented in Fig. 6 can reveal the most widely used measures correlated with SA: SART and subjective workload for self-reported measures; trajectory and braking behaviour for vehicular measures; hands-on reaction time, pedal reaction time, time to reach target speed, lane exceedance, and gaze patterns (e.g., on mirrors, speedometer, and human-machine interface) for behavioural measures; and EEG for physiological measures.

Figure 6 references relevant studies that can guide researchers in both designing the study and ensuring consistency for later comparative analysis. To ensure realism, other parameters such as environmental settings can reflect typical conditions seen during the transition phase of automated driving to manual control, as illustrated in Fig. 4a. These include clear weather, dry roads, daylight, no unusual road conditions, and a moving vehicle on a straight path.

7. Conclusions

This paper summarises and analyses the state-of-the-art research on consideration of driver's reaction in ADS-equipped vehicles during control transitions. The main outcomes of this paper involve developing methodological frameworks for research within the domain of ADS-equipped vehicles. This is achieved by considering the driver's reaction through (1) reviewing major research on driver's reaction during the transition of control, (2) analysing collisions involving ADS-equipped vehicles in California:

- Main parameters and variables that impact the reaction of ADS-equipped vehicle drivers during the transition of control were extracted and analysed based on major past experimental scenarios (see Section 4). Some of the identified research gaps include (i) the assessment of driver reactions using physiological sensors; (ii) determining the optimal timing and method for issuing take-over requests to ensure a safe and timely transition; (iii) conducting real-world experiments; (iv) evaluating the effectiveness of vibrotactile and non-vibrotactile haptic alerts and comparing them to visual and auditory alerts; (v) understanding the impact of various types of tactile actuation; and (vi) investigating the relationship between certain human factors, such as situational awareness, and driver reactions during control transitions. The identified dependent and independent variables can serve as a foundation for designing future experiments in this field.
- California's reports on on-road collisions involving ADS-equipped vehicles during control transitions were analysed (see Section 5). It was found that in 21.6% of these collisions, the ADS-equipped vehicles were in the transition mode when at fault (see Fig. D.1). This highlights the importance of the reaction of the ADS-equipped vehicle's driver at the time of the take-over request. Comparing this analysis with the one in Section 4, we identified several variables (e.g., weather, lighting conditions, road surface, and road user type) that should be considered in future research. We also recommend including data about the cause of the collisions in such reports.
- Our review of literature (see Tables 1 and 3) highlights that the most frequently investigated independent variables were non-driving-related tasks, alert type, take-over time budget, and movement preceding collision. In contrast, variables such as training and system knowledge, environmental factors, and the presence of other road users were rarely examined. A similar imbalance was found in dependent variables, where behavioural and vehicular measures were most common, while physiological responses were notably underrepresented. These findings point to research gaps in both independent and dependent variable coverage. When compared with the real-world collision data analysis (Section 5, Table 2), which showed significant effects of rarely studied variables like other road users, it becomes evident that these underexplored areas warrant further investigation. To illustrate how this insight can inform future research, we also present a case study in Section 6.G demonstrating its application

in scenario design.

- The frequency of independent and dependent variable combinations identified in our meta-analysis (see Table 4) points to underexplored areas in the literature. Some combinations, such as (training and system knowledge, self-reported measures), (training and system knowledge, physiological measures), (other road users, self-reported measures), and (other road users, physiological measures) remain underrepresented in the literature, highlighting potential research gaps (Section 6, Table 4). Particularly, combinations involving variables that significantly effect real-world collision outcomes warrant further investigation. To illustrate practical application, a scenario design case study has been included in Section 6.G.

In conclusion, a comprehensive overview of the identified dependent and independent variables from the above two studies is shown in Fig. 6. Recognising these variables and parameters, along with their detailed classification, aids in designing a variety of experimental scenarios to evaluate the quality of driver reactions in ADS-equipped vehicles during control transitions. This will help bridge the gap between simulated and real-world testing.

Acknowledgment

This work is supported by the Engineering and Physical Sciences Research Council (grant numbers EP/R037795/1 and EP/S01800X/1) and the UKRI Trustworthy Autonomous System HUB (grant number EP/V00784X/1).

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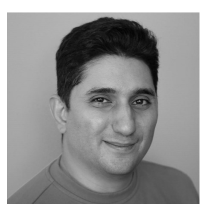

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Appendix A. Data repositories and search terms

TABLE A.1: Data repositories and search terms

Repository	Search term(s)
Web of Sciences	TS=(”transition of control” OR ”transfer of control” OR ”take over” OR “takeover”) AND TS=(”Automated driving systems” OR ”Automated driving system” OR ”Automated driving” OR ”Autonomous vehicle” OR ”Autonomous vehicles” OR”Autonomy level 3” OR ”Conditionally automated” OR ”Driving automation” OR ”Highly automated driving” OR “Partially automated”)
Science Direct	(”transition of control” OR ”transfer of control” OR ”take over” OR ”takeover”)AND (”Automated driving system” OR ”Automated driving” OR ”Autonomous vehicle”)
Google Scholar	allintitle: (”transition of control” OR ”transfer of control” OR ”take over” OR ”takeover”) AND (”Automated driving” OR ”Autonomous vehicle” OR ”Autonomous vehicles” OR ”Autonomy level 3” OR ”Conditionally automated” OR ”Driving automation” OR ”Highly automated” OR ”Partially automated”)
Pubmed	(”transition of control” [tiab] OR ”transfer of control” [tiab] OR ”take over” [tiab] OR ”takeover”[tiab]) AND (”Automated driving systems”[ti] OR ”Automated driving system”[ti] OR ”Automated driving”[ti] OR ”Autonomous vehicle”[ti] OR ”Autonomous vehicles”[ti] OR ”Autonomy level 3” [ti] OR ”Conditionally automated” [ti] OR ”Driving automation” [ti] OR ”Highly automated driving” [ti] OR ”Partially automated” [ti])
IEEE Library	”transition of control” OR ”transfer of control” OR ”take over” OR “takeover”) AND TS=(”Automated driving systems” OR ”Automated driving system” OR ”Automated driving” OR ”Autonomous vehicle” OR ”Autonomous vehicles” OR”Autonomy level 3” OR ”Conditionally automated” OR ”Driving automation” OR ”Highly automated driving” OR “Partially automated”
ACM Digital Library	[[Title: ”automated driving systems”] OR [Title: ”automated driving system”] OR [Title: ”automated driving”] OR [Title: ”autonomous vehicle”] OR [Title: ”autonomous vehicles”] OR [Title: ”autonomy level 3”] OR [Title: ”conditionally automated”] OR [Title: ”driving automation”] OR [Title: ”highly automated driving”] OR [Title: ”partially automated”]] AND [[Abstract: ”transition of control”] OR [Abstract: ”transfer of control”] OR [Abstract: ”take over”] OR [Abstract: ”takeover”]]
SAGE	(”Automated driving systems” OR ”Automated driving system” OR ”Automated driving” OR ”Autonomous vehicle” OR ”Autonomous vehicles” OR ”Autonomy level 3” OR ”Conditionally automated” OR ”Driving automation” OR ”Highly automated driving” OR “Partially automated”) AND (”transition of control” OR ”transfer of control” OR ”take over” OR ”takeover”)

TABLE B.1

APPENDIX B. PARAMETERS USED IN STUDIES RELATED TO THE TRANSITION OF CONTROL IN ADS-EQUIPPED VEHICLES IN DRIVING SIMULATOR STUDIES

No.	Ref.	Participants	Road Type	Experiment's Length [min]	Alert Type	Manual Driving Duration [min]	Automated Driving Duration [min] or Length [km]	TOT budget [s]	Manual Driving Speed [$\frac{km}{h}$]	Automated Driving Speed [$\frac{km}{h}$]	NDRT*
1	[150]	17	2-lane	35	AV	5 [min]	5 or 30 [min]	10	110	110	Writing, watching video, closing eyes
2	[151]	44	2-lane	65	A-V	10 [min]	55 [min]	3	*Notknown*	*Notknown*	
3	[152]	37	2-lane	105	A-V	Not known	$***$ [min]	14-24	Not known	70-50	Visual-cognitive
4	[153]	44	3-lane	10	A-V-T	Not known	10 [min]	6	Not known	110	Playing by phone
5	[137]	74	2-lane	75	AV	Not known	Not known	Not known	Not known	Not known	Visual-cognitive
7	[134]	346	2-lane	Not known	A-V, V-T, A-V-T	Not known	Not known	Not known	Not known	Not known	visual 2-back, auditory 2-back, no task
8	[16]	33	3-lane	90	A-V	Not known	2.5 [km]	8	Not known	100	Copying string of text
9	[154]	32	2-lane	43	ANV	Some seconds	2.5 to 7.5 [min]	4, 8	Not applicable	60, 80, 100	SuRT
10	[55]	56	2-lane	30	ANV-V	Some seconds	30 [min]	9, 18	Not known	50 to 70	Reading
11	[155]	18	2-lane	35	ANV	7-8 [min]	10, 14 [min]	4, 5	130	130	Simon game*
12	[156]	16	3-lane	84	AV	Up to 2 [min]	5 [min]	5	112	112	Arrow task*
13	[157]	41	1-lane	80	AV	Not known	Not known	Not known	20-80	20-80	Play games
14	[84]	45	2-lane	40	ANV	1	5, 15, 30 [min]	10	110	110	None
16	[85]	48	6-lane	19[km]	ANV	1.5 [km]	3 [km]	5 or 7	110	110	SuRT
17	[159]	39	Various	8	AV-V	Some seconds	1 [min]	20	48, 96	48, 96	Reading
18	[76]	52	2-lane	Not known	ANV-V	1.6 [km]	7.5 [km]	8, 45	50	50	Akinator game*
19	[160]	25	2-lane	10	ANV	Some seconds	1 [min]	2.5, 3, 3.5, 4, 4.5	Not applicable	100	No task
23	[126]	42	2-lane	90	ANV	Not known	1.5 [min]	Not known	130	130	None
24	[162]	53	Not known		ANV-V, AV-V	Not applicable	Not applicable	8, 16	Not applicable	Not applicable	Texting
25	[79]	32	1-lane	36	A-V	Some seconds	8 [min]	4	56	56	Watching video
26	[100]	20	2/3/4-lane	18-20	V, ANV, T, ANV-V, ANV-T, V-T	0.5 [km]	Not known	7	60-80	Not known	No task, phone, watching video
27	[115]	60	2/3-lane	Not known	ANV-V	5 [min]	5	5.25	Not known	120	Reading, Tetris
28	[97]	12	3-lane	40	ANV-V	Not known	Not known	Not known	Not known	Not known	Drinking
29	[17]	36	3-lane	135	V-AV-ANV	Some seconds	2.5 to 7.5 [min]	10	Some seconds	130	RSVP*
30	[83]	30	3-lane	45	A**	Not known	5/20	6	Not applicable	120	SuRT
31	[163]	34	3-lane	3.63	V	3.46 [min]	Not applicable	Not applicable	100	Not applicable	No task
32	[60]	24	3-lane	Not known	ANV**,T**,ANV-T**	*Notknown*	*Notknown*	7	100	120	SuRT*
33	[75]	75	3-lane	Not known	ANV-V	Not known	20	3	Not Known	112	Quiz, n-back task*
34	[51]	26	3-lane	50	AV-V	2 [min]	20	Not applicable	112	112	Reading
35	[62]	18	3-lane	Not known	T	2 [min]	1.5	7	0-120	120	n-back task
36	[52]	26	3-lane	30 [km]	AV-V	Not known	Not known	Not known	112	112	Reading
37	[120]	28	2-lane	120	ANV-V	2.5 [min]	10	3	3-45	100-110	NDRT
38	[71]	72	6-lane	80	ANV	Not applicable	Not known	7	Not applicable	120	TQT
39	[87]	32	2-lane	40	No alert	Not known	1	4, 6, 8, 12	48-56	56	Reading
40	[70]	72	3-lane	20	ANV	Not applicable	6	7	Not applicable	120	TQT*
41	[121]	21	3-lane	Not known	ANV-V	No manual driving	0.50-0.66	5	Not known	Not known	1-back task *
42	[72]	79	2/3-lane	30	ANV-V	Not known	3.5, 11.5	2.5, 4	Not known	80, 120	Writing, reading, watching video
43	[116]	65	3-lane	Not known	ANV-V**	Not applicable	Not known	7	Not applicable	120	SuRT*
44	[119]	21	1-lane (rural)	60	AV**, V, T, AV-V, AV-T**, V-T**, AV-V-T**	0.16 [min]	0.45-0.53	Not known	Not known	112	Tablet game
45	[59]	48	1-lane (rural)	40	V	Not known	8.5	20+5	Not known	Not known	Reading, watching a movie
46	[68]	30	2-lane	70	AV-V**	8 [km]	2-4	4, 6	Not known	80	Watching a video
47	[118]	23	6-lane	38	ANV	Not applicable	5	10	Not applicable	80	SuRT
48	[63]	26	5/2-lane	3	ANV-T	0.416 [min]	Not known	Not known	Not known	64-88	Texting on a phone
49	[82]	16	3-lane	2	ANV	0.5 [min]	1	6.5	108	Not known	Reading aloud
50	[64]	44	2-lane	Not known	ANV-V	Not known	Not known	10	Max 100	60-80	Quiz game
51	[57]	24	3-lane	45	AV-V	Not known	Not known	7.78	108	108	SuRT, Texting, 2-Back task *
52	[91]	89	2-lane	28	ANV-V	5 [min]	8, 11	4.9, 5.7, 6.6, 12	Not known	130	Texting, internet search
53	[58]	16	3-lane	45	A-V**,V**	Not known	Not known	Not known	Not known	50	Reading
55	[61]	46	3-lane	Not known	ANV-V	Not known	8	7	Not known	120	SuRT
56	[124]	34	3-lane	88 [km]	V	2 [km]	Not known	Not known	Not known	Not known	Not known
57	[117]	48	3-lane	Not known	ANV-V	Not known	Not known	Not known	Not known	120	SuRT
58	[73]	48	3-lane	Not known	ANV-V	Not known	Not known	7	Not known	120	2-back task,SuRT
59	[66]	49	3-lane	Not known	ANV	Not known	Not known	5, 7	Not known	120	SuRT
60	[125]	29	1-lane	Not known	Not applicable	Not known	Not known	2-2.4	Not known	75	No task
61	[92]	48	3-lane	28	ANV-V	Not known	4	6	Not known	120	SuRT
62	[67]	34	2-lane	60	ANV	1.5	15-20	1.5, 2.2, 2.8	Not known	60	Blue dot game
63	[110]	32	3-lane	60	A	Not known	4	4, 6, 8	Not known	100	Target tracking on screen
64	[56]	24	3-lane	Not known	ANV-V,AV-V	10 [min]	10	200m	70	Not known	In-vehicle information system

* and **: See Footnote of Table 1.

Appendix C: Definition and frequency of dependent variables in literature

TABLE C.1: Dependent variables (KPIs) and their definitions.

Dependent variables/KPIs [unit]	Description	Ref.
behavioural measures		
Gaze RT* [s]	Time between TOR* and first glance be away from non-driving-related task	[83], [111], [115]
Road fixation time [s]	Time between TOR and the driver first glance fixes at the scenery	[116], [122], [123]
Side mirror gazing time [s]	Time between TOR and the driver glances at the side mirror	[61], [66], [92], [115]
Speedometer gazing time [s]	Time between TOR and the driver glances at the speedometer	[115]
Average duration of gazes [s]	Average time the driver gazes towards the area of interest per gaze	[83]
Cumulative duration of gazes [s]	Time the driver is looking to area of interest	[74], [83], [91], [121]
Max* duration of one gaze [s]	Max time the driver gazes towards the area of interest in one gaze	[83]
Horizontal gaze dispersion [m]	Deviation of horizontal gaze position	[70]
Percent road centre	Percentage of gazes on the road centre in a given time frame	[124], [125]
Distribution of gazes	Percentage of gazes per area of interest (e.g. side mirrors, etc)	[63], [74], [82], [120]
Number of gazes	Total amount of gazes towards area of interest	[63], [83], [121]
Glance rate in the target zone	If driver glances into the area of interest, the score is 1	[87]
Hands-on RT [s]	Elapsed time from TOR until the driver takes hands on the steering wheel	[71], [111], [115]
Movement time [s]	Time between TOR and the driver starts to move a hand	[116]
Button press RT [s]	Time between TOR pressing a button on steering wheel	[59], [119]
Steer initiate RT [s]	Time between TOR and the driver initiates a steer turn (0.25 deg)	[60], [62], [82], [121]
Steer turn RT [s]	Time between TOR and the driver performs a steering turn (2 deg)	[60], [62]
Pedal RT [s]	Time until driver starts to brake or accelerate	[62], [63], [115]
Turn signal RT [s]	Time until the driver uses the indicator	[60], [66], [92]
Min intervention RT [s]	Min time driver needs to react to a TOR (e.g. steering)	[62], [66]
Car avoid RT [s]	Time until the deviation from the lane centre is greater than 1 m.	[59], [62]
Min time to line crossing [s]	Time until line is crossed (not further specified)	[74]
Lane change RT [s]	Time until the deviation from lane centre is greater than 2 m.	[62], [63], [82]
Min time to collision [s]	Remaining time to collision in take-over situation	[70], [83], [121]
Remaining action time [s]	Time that theoretically remains until collision, from first intervention	[66]
Time headway [s]	Time between the participant's an the merging vehicle	[126]
Take-over time [s]	Time between a human driver receiving a TOR and their take-over reaction	[16]
Distribution of reaction types [%]	Percentage of using different types of reaction (e.g. braking, steering)	[61], [64], [82]
Amount of collisions [%]	Total number/ percentage of collisions with an obstacle in given situation	[67], [71], [91]
Correct response rate of vibrotactile patterns [%]	Percentage of correct responses to warnings issued through vibrotactile pattern in seat	[62]
Response accuracy [%]	Correct actions performed when asked by the system	[119]
Transition of control [%]	The action of taking back/over control when asked to	[56]
Rate of lane change errors	Wrong gaze behaviour and use of indicator during lane change	[61], [116]
Driving errors	Total number of wrong, late or no lane changes when required	[110]
Choice of lane	Total number of choosing the risky lane during a lane change	[63]
Lane exceedance	Amount of lane exceedance occurrences	[125]
Driver drowsiness	Yawning or extended eye closure	[59]
Occurrence of system warning	Total number of system warnings	[97]
Testing the boundaries	Drivers intentionally test the limits of automated functionality	[97]
Mode confusion	Driver says driving automation system is in one mode when it is actually in another	[97]
Engagement in NDRTs*	Any activity not associated with the driving task	[97]
Vehicular measures		
SD* of lateral displacement [m]	SD of lateral position after TOR was issued	[52], [72], [115], [120]
Max lateral position [m]	Max deviation from the centre of the lane after TOR was issued	[58]
Min headway distance [m]	Min distance to obstacle which the situation becomes non-critical	[59]
Max steering wheel angle [rad]	Max steering wheel angle during situation	[117]
Mean speed [m/s]	Mean speed during (parts of) the drive	[56], [124]
Min speed [m/s]	Min speed during (parts of) the drive	[124]
SD of steering angular rates [m/s]	SD of steering angular rates	[51], [52]
Max lateral Acc [m/s^2]	Max lateral Acc during situation.	[57], [71], [72], [82], [83]
Max longitudinal Acc [m/s^2]	Max longitudinal Acc during situation.	[70], [71], [83], [116]
Max resulting Acc [m/s^2]	Max resulting Acc during situation (longitudinal and lateral Acc)	[61], [116], [117]
Braking behaviour	Percentage of braking in the scenario (no action, off throttle, braking)	[63], [68], [125]
Acc behaviour	Total number of Acc pedal usages	[63]

continued …

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Dependent variables/KPIs [unit]	Description	Ref.
Trajectories	Trajectories printed in a graph to review the driving performance	[61], [92], [110]
Speed profile	Assessing if the driver did not go too fast or too slow	[63]
Self-reported measures		
Subjective workload	NASA-TLX questionnaire to assess the workload	[52], [60], [62], [121]
Mental workload	16-point scale ranging from not demanding to very demanding	[115]
Usefulness	Usefulness was assessed on a 5-point Likert scale	[60], [62], [162]
Satisfaction	Satisfaction was assessed on a 5-point Likert scale	[60], [62], [63]
SAGAT questionnaire	Situation awareness global assessment technique questionnaire	[67], [74]
SART questionnaire	Situation awareness rating technique questionnaire	[67]
Comfort of take-over	Likert scale ranging from very stressful (1) to very comfortable (7)	[64], [64], [110]
Ease of take-over	Assessment on the take-over task (easy, stressful, overwhelming)	[68]
Take-over performance	Self-reported explanation on performance in hazardous situation	[68]
Take-over strategy	Self-reported explanation of how take-over is achieved	[68]
Performance in NDRT	Assessing engagement in non-driving-related task	[68]
Driver's behaviour	Video analysis of driver's reaction to TOR	[64]
Controllability	Own perception of control of the vehicle on an 11-point scale	[73]
Driving performance	Perception of safety using different kinds of human-machine monitoring state evaluation interfaces	[56]
Criticality	Perception of criticality of current situation by driver	[73]
Take-over readiness	To which extent participants were ready to take over control of the vehicle when a TOR was issued	[47], [111]

* RT = Reaction Time, TOR = Take-Over Request, Max = Maximum, Min = Minimum, NDRT = Non-Driving-Related Task, SD = Standard Deviation.

Appendix D: DMV collision analysis (2014-2023) for ADS-equipped vehicles versus other road users at fault

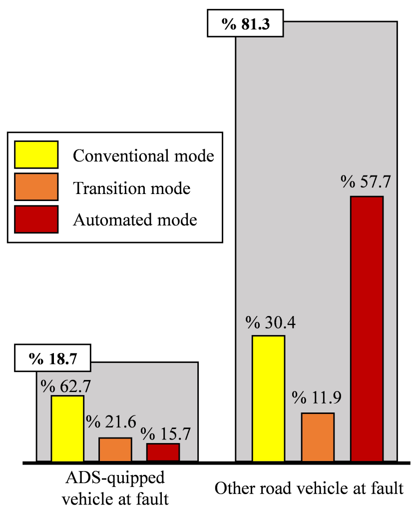

Fig. D.1. Classification of collisions involving ADS-equipped vehicles in DMV reports between October 2014 and January 2023 [29] based on potential causer of the collision: (a) the ADS-equipped vehicle at fault, and (b) the other road users at fault.

Appendix E: Classification of collisions in DMV reports

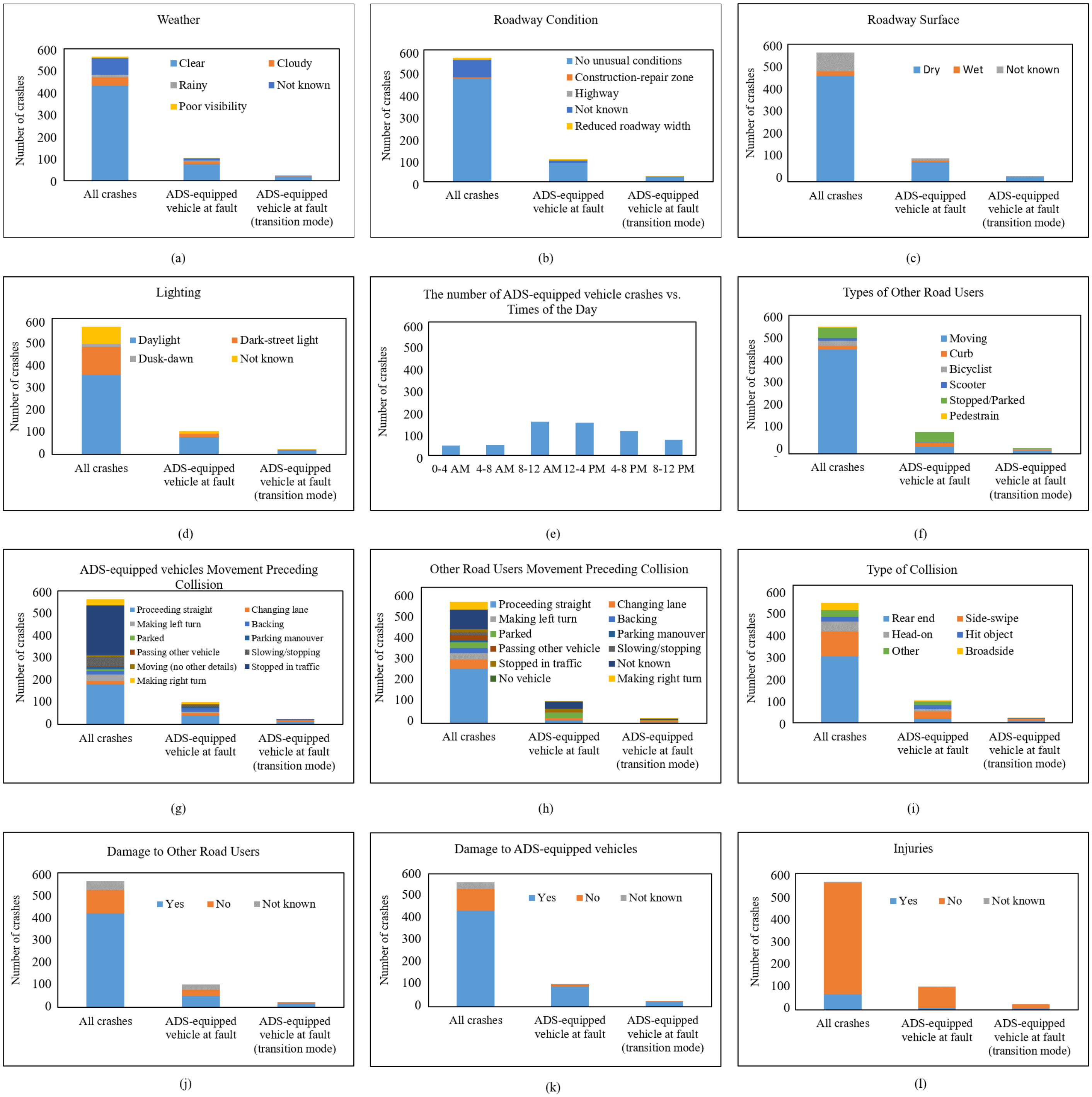

Fig. E.1. California DMV reports on collisions involving ADS-equipped vehicle are analysed based on: (a) Weather conditions, (b) Roadway conditions, (c) Roadway surface, (d) Road lighting, (e) Status of the ADS-equipped vehicle, (f) Status of the other road users, (g) ADS-equipped vehicle movement preceding collision, (h) Other road users movement preceding collision, (i) Type of collision, (j) Damage to the other road users, (k) Damage to ADS-equipped vehicle, and (l) Injuries.