Takeover Context Matters: Characterising Context of Takeovers in Naturalistic Driving using Super Cruise and Autopilot

Shiyan Yang*
Shiyan.Yang@seeingmachines.com
Human Factors
Seeing Machines
Canberra, Australia

Angus McKerral
Human Factors
Seeing Machines
Canberra, Australia

Megan D. Mulhall
Human Factors
Seeing Machines
Canberra, Australia

Michael G. Lenné
Human Factors
Seeing Machines
Canberra, Australia

Pnina Gershon
MIT Age Lab
Massachusetts Institute of Technology
MA, USA

Bryan Reimer
MIT Age Lab
Massachusetts Institute of Technology
MA, USA

ABSTRACT

Takeover safety is a critical issue when using Level 2 advanced driver assistance systems. Understanding the context of takeover can facilitate the development of driver monitoring systems that can adapt to changing environments for more contextually appropriate assistance during takeover. The paper presents a hierarchical clustering analysis of hundreds of post-takeover vehicle kinematics in the MIT-AVT naturalistic driving study. Results show similar types of takeovers between Super Cruise and Autopilot: normal takeover, braking takeover, accelerating takeover, evasive-manoeuvre takeover, and right-swerve takeover (Autopilot only). Context analysis showed that braking takeover which occurred at a normal highway speed was often associated with upcoming highway exits and foreseeable low-speed situations, while accelerating, evasive-manoeuvre, and right-swerve takeovers were caused by strong brake (for Super Cruise) or large steering (for Autopilot) during slow car following. The findings indicate the potential for sensor-based approaches to assessing various contexts and facilitating a more holistic takeover reference model.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; *HCI theory, concepts and models.*

KEYWORDS

Takeover, context, Level 2 ADAS, naturalistic driving, hierarchical clustering

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1 INTRODUCTION

Vehicles equipped with Level 2 advanced driver assistance systems (ADAS) [1], such as Cadillac's Super Cruise and Tesla's Autopilot, are becoming more and more popular in the automotive market. ADAS features provide steering and acceleration/brake support to the driver, which have been shown to lead to misuse such as hands-free and feet-free driving even when these behaviours are not supported by the system [3, 27]. Ironically, ADAS use creates a propensity for drivers to become distracted, inattentive, or out-of-the-loop [10, 23], despite regulatory requirements and manufacturers' guidance for drivers to supervise ADAS [14]. This irony of automation can impair drivers' readiness for machine-initiated transfers of control (TOCs; i.e., the process that the driver takes over control of the vehicle after ADAS disengagement), which has been proven by extensive research from the human factors community [15, 33, 35].

To support readiness of TOCs, driver monitoring systems (DMS) are used to keep drivers "in-the-loop" (i.e., in physical control of the vehicle and monitoring the driving situation; [25]). For example, Tesla vehicles rely on steering-based sensors to detect "hands-on-wheel" through small resistance of the steering wheel, while Cadillac vehicles adopt camera-based DMS to monitor driver gaze direction to ensure visual attention is directed towards the roadway. Since camera-based DMS explicitly assess driver visual attention, they are more difficult to be circumvented by drivers compared with steering-based DMS (e.g., [30]). Although eye tracking alone serves as an important safety function, it can be more effective to support takeover if combined with vehicle dynamics and driving context to assess attention allocation in relation to dynamic driving environments (e.g., high vs. low speed, heavy vs. light traffic).

Therefore, it is necessary to understand the context of takeover in the real world. Since driver-initiated TOCs are much more common than machine-initiated TOCs in the real world [15, 26], these takeovers are more easily associated with a variety of contextual factors. Although driver-initiated TOCs are normally not as safety

*Corresponding author

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critical as machine-initiated TOCs [26], they reflect ecological interaction among driver, machine, and driving environments, suggesting that a more generalisable reference models may be derived from these takeovers to determine more- or less-risky takeover scenarios (e.g., curved vs. straight roads; [6]) and high or low takeover quality specific to a given context [7]. If this measurement can be paired with accurate monitoring of driver distraction and other adverse states, DMS then can become more adaptable to driving environments to create better mitigation strategies for high-risk TOCs [12, 19].

Recent interviews among Tesla drivers have shed light on a list of factors contributing to driver-initiated disengagement of Autopilot [29]. Drivers disengage Autopilot when they observe unwanted actions (e.g., harsh deceleration, following a slower vehicle, driving on unfamiliar roads), or believe that automation is unsuitable for certain environments (e.g., non-standard roads, curves, hills, on/off-ramp, lane merging, and splitting situations). Moreover, Autopilot disengagement is associated with travel trip constraints (e.g., travel time and distance). Additionally, random disengagement can happen (e.g., when drivers are not aware of the reasons underlying disengagements). The variety of driver-initiated TOCs cannot be analysed in experimental paradigms that were predominantly developed to study machine-initiated TOCs – they made use of a single scenario repeated across participants in order to generate statistically comparable data. Therefore, different approaches are needed to understand how drivers interact with ADAS with various styles of takeover and in response to real-world takeover contexts.

Compared with experimental paradigms, naturalistic driving studies offer novel opportunities to understand the diversity of TOCs. These studies have been lacking until a recent wave of naturalistic TOC studies, which compared driver gaze locations and steering wheel control levels before and after TOCs (e.g., [15, 26, 27]), and vehicle kinematics among the strategic, manoeuvre, and control TOCs [16]. However, there is still little known about how the transition control behaviours are associated with driving contexts in the wild. This gap motivates our research focused on understanding the relationship between driver-initiated takeover and diverse, naturalistic scenarios, particularly based on sensing signals (CAN Bus, GPS, and videos). Specifically, this paper attempts to answer the following questions:

(1) In naturalistic driving, how many types of takeovers can be meaningfully identified in terms of post-takeover vehicle control?
(2) What are the characteristics of each type of takeover performance?
(3) How does each type of takeover associate with the identified contextual factors?

The paper presents an analysis of takeovers in the MIT-AVT naturalistic driving study [13], which to date has involved the collection of over 750,000 miles of data in vehicles equipped with Level 2 ADAS systems. Contextual factors were extracted from camera videos (traffic), CAN Bus signals (vehicle kinematics), and GPS data (road rank) within a certain period before and after each TOC. Associations between the contextual factors and takeover groups were analysed to illustrate the interaction among driver, machine, and environments. The knowledge facilitates context-based modelling and assessment of takeover performance and safety.

2 METHOD

2.1 Naturalistic Driving Data

Data were sampled from eight male drivers driving Cadillac CT6 equipped with Super Cruise, and eight male drivers driving Tesla Model S/X. Table 1 shows their age and trip information. The trips of CT6 mainly took place across the Northeastern United States while the trips of Model S/X were found in multiple eastern, central, and southern states.

2.2 Data Processing

During naturalistic driving, data were recorded continuously from multiple sensors, including inward and forward-facing cameras, CAN Bus, and GPS. The status of ADAS (on vs. off) from CAN Bus was used to identify 214 takeover events from Cadillac driving and 525 takeover events from Tesla driving. Each event was sampled to included a minimum period of at least 10s ADAS engagement followed by 10s manual driving.

2.2.1 Vehicle Kinematics. Within 10s following ADAS disengagement, drivers' vehicle kinematics was measured by several metrics chosen from a comprehensive list of takeover performance metrics [9, 21]. They were:

- Vehicle speed at ADAS disengagement (mph);
- Speed change (i.e., difference between the maximal and minimal speeds in mph, with the later one minus the early one; increase +, decrease –);
- Maximal longitudinal acceleration (+) and deceleration (–; m/s^2);
- Maximal steering wheel angle to left (–) and right (+; °);
- Maximal steering wheel angle speed to left (–) and right (+; °/s; used for Super Cruise vehicles);
- And maximal lateral acceleration to left (–) and right (+; m/s^2; only available for Tesla vehicles).

2.2.2 Lead-car Proximity. Lead-car proximity was used to approximate headway distance (not time gap) to the lead car. Surrounding vehicles in the forward-facing videos were detected as bounding boxes by YOLOv5l (confidence threshold=0.4, IoU threshold=0.5) that was pretrained on the COCO dataset [22]. YOLOv5l was operated on NVIDIA's GeForce GTX 1080. The lead-car proximity was calculated as the percentage of the centre region of the video occupied by the union area of all bounding boxs within that region [32, 34]. The centre region was empirically chosen to cover the forward lane without overly covering the adjacent lanes. For Cadillac drivers, the centre region was outlined by vertical boundaries at 384 px and 704 px or 448 px and 768 px; for Tesla drivers, the centre region was outlined by the vertical boundaries at 512 px and 896 px or 384 px and 768 px (see Figure 1). Different boundary settings of centre region were used to offset the variation of camera angels in the instrument vehicles.

2.2.3 Road Type. Road type was retrieved from OpenStreetMap according to the latitude and longitude. Road type analysis was complete in Python package Osmnx, which is a tool for acquiring,

Table 1: Driver demographics and trip information.

Vehicle	n	Mean Age (Range; SD)	Number of trips per driver	Total Driving Hours	Driving Period
Cadillac CT6 (Super Cruise)	8	43 (30-60; 12)	20~40	201.3	2018-2021
Tesla Model S/X (Autopilot)	8	42 (39-60; 12)	50	477	2016-2018

Note: Mean age is the driver age at the earliest trip.

Figure 1: Example of lead-car proximity estimation from the forward-facing video. The blue vertical lines outline the front region.

constructing, and analysing complex street networks [5]. The road types match with U.S road ranks and were simplified into four categories: freeway (limited access freeway), highway (limited access highway, primary highway, and secondary highway), non-highway (tertiary route, other roads) and link (connection between different types of road). It is worth noting that when driving through intersections, the tracking algorithm may recognise the intersecting road as the nearest edge to generate road type. Since this type of error was normally very short (1~3s; due to the vehicles' quickly passing), it was corrected based on the stable road type before and afterwards. Additionally, speed limit was also retrieved from OpenStreetMap. Mean vehicle kinematics (30 Hz) and mean lead-car proximity (30 Hz) within each second was synchronized with road type and speed limit (1 Hz) for all trips.

2.3 Takeover Clustering

Agglomerative hierarchical clustering (AHC; Python package scipy.cluster.hierarchy [4, 28]) was used to classify takeover events into different categories based on vehicle kinematics metrics in the 10s following ADAS disengagement. AHC is a bottom-up approach that treats each observation as its own cluster at the beginning, and then combines the clusters as one based on the "distance" between two clusters when moving up the hierarchy. The distance was calculated by Ward variance minimization algorithm (also called Ward's method), which computes how much the sum of squares will increase when the two clusters are merged (see Equations 1 and 2). All features were normalised for clustering.

$$d(u,v) = \sqrt{\frac{|v|+|s|}{T} d(v,s)^2 + \frac{|v|+|t|}{T} d(v,t)^2 - \frac{|v|}{T} d(s,t)^2} \quad (1)$$

$$T = |v| + |s| + |t| \quad (2)$$

where u is the newly joined cluster consisting of clusters s and t, v is an unused cluster. $|*|$ is the cardinality of the argument. The optimal cluster numbers were determined by visual inspection of the dendrograms.

2.4 Contextual Factors

The decision to initiate a TOC may be informed by contextual factors prior to ADAS disengagement or anticipated events that occur much later than ADAS disengagement. Six metrics were used to assess driving context within 10s before takeover and two metrics were used to search upcoming highway exits and the need of significantly slowing down the vehicle (often due to traffic or sharp turn) within 1 min after takeover (see Figure 2). The 1-min window was empirically chosen to represent a timeline in which the events were foreseeable from the point of ADAS being disengaged.

The metrics of contextual factors prior to takeover are described in Table 2.

2.5 Statistical Analysis

Kruskal-Wallis (KW) tests [18] were used for statistical comparisons of contextual factors among different takeover groups due to its capability of handling non-parametric and imbalanced data [17]. Dunn tests were used for post hoc analysis. The analysis was conducted using R package "dunn.test" [11].

3 RESULTS

3.1 Takeover Clustering

Dendrograms illustrate that the optimal clustering number for takeovers related to Super Cruise and Autopilot is four and five, respectively (see Figure 3).

3.2 Categories of SC-related Takeover

Figure 4 shows the characteristics of the four groups of SC-related takeovers. Group1 includes 143 takeovers (from 8 drivers) at a mean speed of 62.8 mph followed by small lateral and longitudinal movements. Group 2 includes 52 takeovers (from 7 drivers) at a mean speed of 57.5 mph but followed by strong deceleration (maximal deceleration=-4.85 m/s^2). Group 3 includes 12 takeovers (from 6 drivers) at an abnormally low speed (24.4 mph) followed by strong acceleration (maximal acceleration=3.51 m/s^2). Group 4 includes 7 takeovers (from 3 drivers) at an abnormally slow speed (12.4 mph) followed by strong deceleration (maximal deceleration=-3.31 m/s^2) and steering wheel rotation (maximal angle=11.43° to right and -9.29° to left).

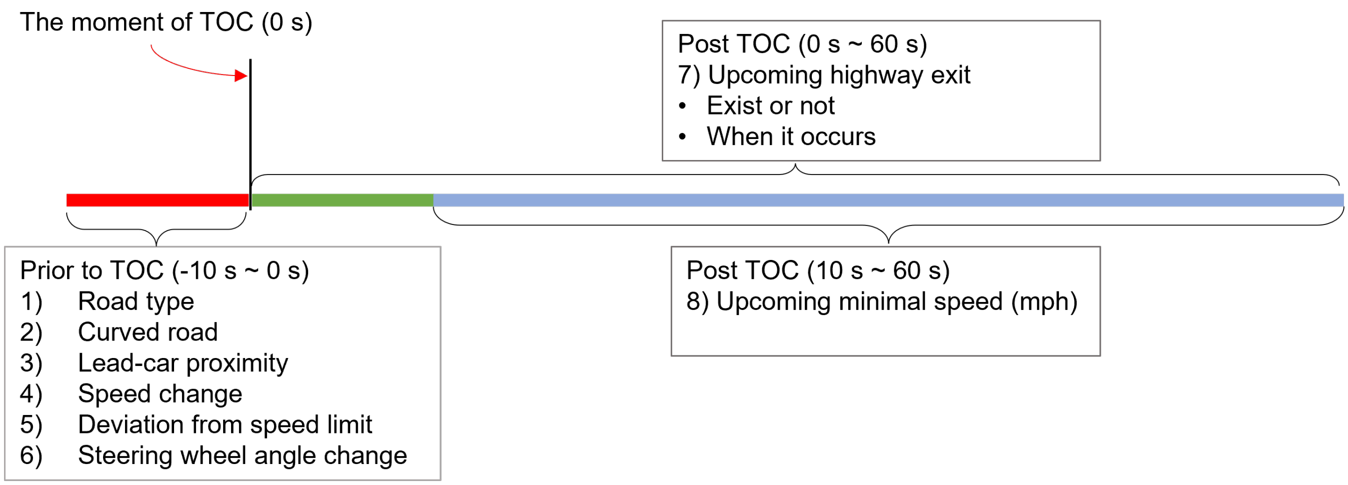

Figure 2: Metrics of contextual factors before and after TOC.

Table 2: Metrics of contextual factors before and after takeover.

Metric	Description
Road type (freeway, highway, non-highway, link)	Road type assessed by GPS on OpenStreetMap.
Curved road (yes or no)	If both maximal and minimal steering wheel angles are either positive or negative, the driver is rotating the steering wheel at one direction over the 10s window, indicating that they are driving on a curved road.
Lead-car proximity (%)	The centre region of the video that is occupied by the bounding boxes of detected vehicles.
Speed change (mph)	Difference between maximal and minimal speed.
Deviation from speed limit (mph)	Minimal vehicle speed minus the speed limit.
Steering wheel angle change (degrees)	Absolute difference between the maximal and minimal steering wheel angles.
Upcoming highway exit (existing or no; if exist, when it happens)	Link or non-highway section ≥ 4s is searched within 1 min window after TOC. If it is not found, search stops either at the end of the 1 min window or the moment when ADAS is reengaged.
Upcoming minimal speed (mph)	When highway exits do not exist, the minimal speed between 10s and 60s after TOC is identified to indicate the potential need of driving slowly.

3.3 Categories of AP-related Takeover

Figure 5 shows the characteristics of the five groups of AP-related takeovers. Group 1 includes 324 takeovers (from 8 drivers) at a mean speed of 63.3 mph followed by limited vehicle lateral and longitudinal movements. Group 2 includes 119 takeovers (from 8 drivers) at a mean speed of 51.5 mph followed by strong deceleration (mean maximal deceleration=-1.99 m/s^2), large speed decrease (-17.3 mph), and large right steering rotation (maximal right steering angle=13.08°). Group 3 includes 42 takeovers (from 7 drivers) at an abnormally low speed (25.9 mph) followed by strong acceleration (maximal acceleration=1.84 m/s^2). Group 4 includes 25 takeovers (from 7 drivers) at an abnormally low speed (mean=18.1 mph) followed by obvious deceleration (maximal deceleration=-1.62 m/s^2) and large left steering rotation (maximal left steering angle=-38.6°). Group 5 includes 14 takeovers (from 5 drivers) at an abnormally low speed (mean=13.9 mph) followed by large right steering rotation (maximal right steering angle=60.5°) and acceleration (0.94 m/s^2).

3.4 Context of SC-related Takeover

GPS data was unavailable from two Cadillac drivers, so takeover events without available GPS were removed, leaving 140 takeover

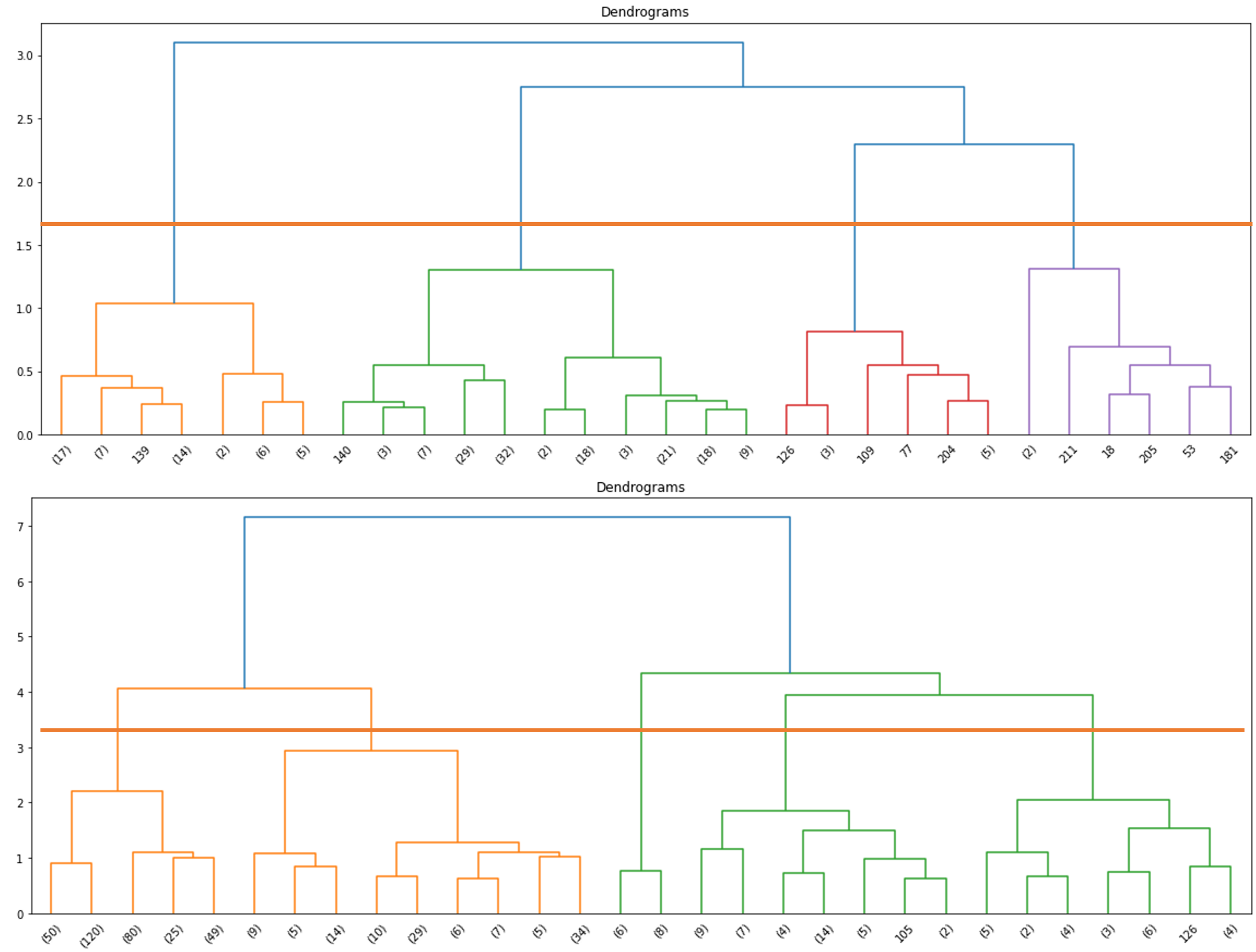

Figure 3: Dendrograms of hierarchical clustering of takeovers related to Super Cruise (top) and Autopilot (bottom).

events for statistical analysis of deviation from speed limit, road type, highway exit, and upcoming slow driving.

Results of KW tests for each contextual factor for SC-related takeover were described below (also see Figure 6).

- *Road type.* 99.3% of SC-related takeovers occurred during freeway or highway driving.
- *Curved road.* It occurred in 56.1%, 46.2%, 44.4%, and 28.6% of the takeovers from Groups 1 to 4.
- *Lead-car proximity.* It was significantly different among takeover groups (χ^2=29.6, df=3, p<.001). Post hoc analysis showed that mean lead-car proximity in Groups 3 (8.2%) and 4 (14.0%) was significantly higher than Groups 1 (4.8%) and 2 (3.9%; p<.001 for all comparisons).
- *Speed change.* Speed change before TOC was significantly different among takeover groups (χ^2=9.42, df=3, p=.02). Mean speed decrease in Group 3 (-11.5 mph) was significantly larger than Groups 1 (-3.1 mph) and 2 (-4.5 mph; p=.002 and p=.024, respectively).
- *Deviation from the speed limit.* It was also significantly different among takeover groups (χ^2=37.6, df=3, p<.001). The mean deviation in Groups 3 (-35.8 mph) and 4 (-44.2 mph) were significantly larger than Groups 1 (1.36 mph) and 2 (-3.00 mph; p<.001 for all comparisons).
- *Steering change.* Steering wheel angle change was not significantly different among takeover groups (χ^2=6.66, df=3, p<.08).
- *Highway exit.* 40.8% (40), 42.3% (11), 33.3 (3), and 14.3% (1) of the takeovers from Groups 1 to 4 involved passing a link or non-highway road within 1 min after Super Cruise disengagement. Starting time of highway exits significantly differed between takeover groups (χ^2=11.0, df=3, p=.001). Compared to Group 1 (mean time gap= 30.1 s), highway exit occurred much closer to TOC in Group 2 (mean time gap=14.5 s; p=.003).
- *Upcoming minimal speed (10s~60s).* It was significantly different among the takeover groups (χ^2=33.7, df=3, p<.001).

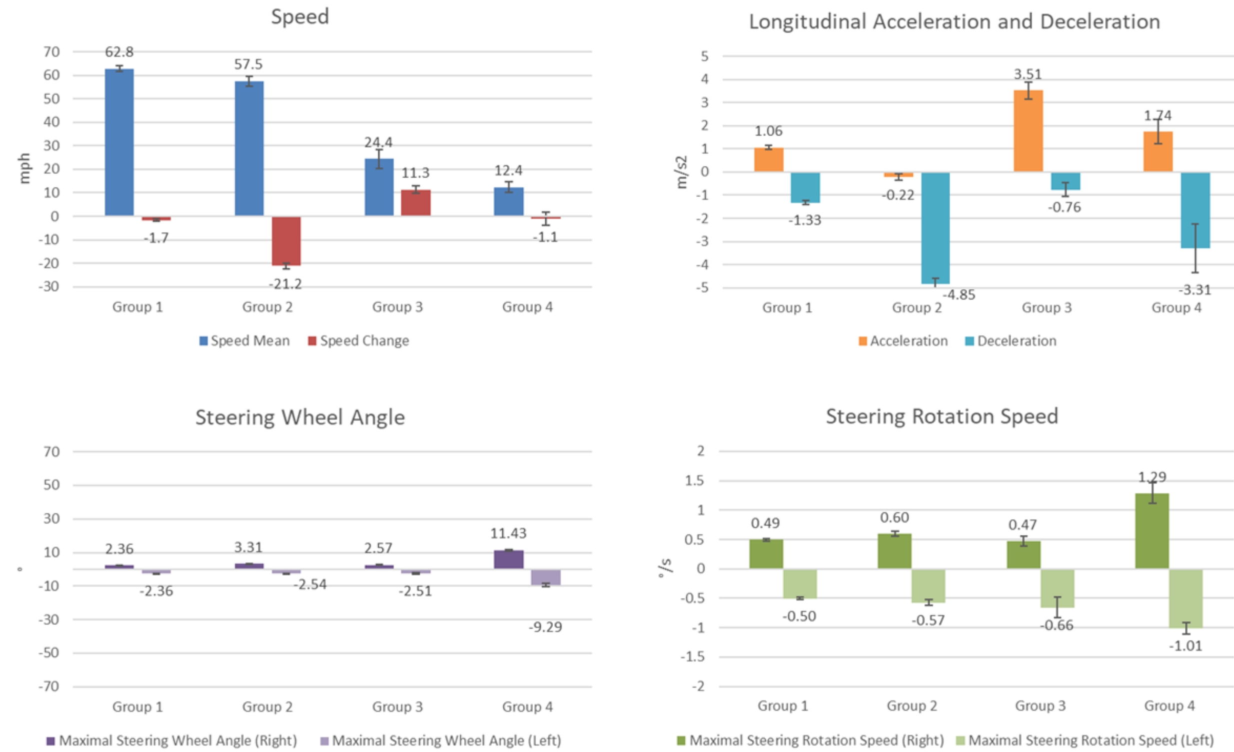

Figure 4: Characteristics of the four categories of SC-related takeovers.

Post hoc tests showed that the upcoming minimal speed was much lower in Groups 2 (18.3 mph; p<.001), 3 (24.8 mph; p<.006), and 4 (5.1 mph; p<.001) than Group 1 (43.9 mph).

3.5 Context of AP-related Takeover

Results of KW tests for each contextual factor for AP-related takeovers are described below (also see Figure 7).

- *Road type.* 92.0% of AP-related takeovers occurred during freeway or highway driving.
- *Curved road.* Curved road occurred prior to 61.4%, 68.9%, 52.4%, 56.0%, and 64.3% of the takeovers from Groups 1 to 5.
- *Lead-car proximity.* It was significantly different among takeover groups (χ^2=103, df=4, p<.001). Post hoc analysis showed that mean lead-car proximity in Groups 3 (10.9%), 4 (13.9%), and 5 (14.8%) was significantly higher than Groups 1 (4.6%) and 2 (4.3%; p<.001 for all comparisons).
- *Speed change.* Speed change before TOC was not significantly different among takeover groups (χ^2=2.86, df=4, p=.58).
- *Deviation from the speed limit.* It was significantly different among takeover groups (χ^2=141, df=4, p<.001). The mean deviation in Groups 3 (-29.0 mph), 4 (-28.7 mph) and 5 (-26.2 mph) were significantly larger than Groups 1 (5.87 mph) and 2 (0.17 mph; p<.001 for all comparisons). Deviation in Group 1 was significantly larger than Group 2 (p=.0035).
- *Steering change.* Steering wheel angle change was also significantly different among takeover groups (χ^2=46.8, df=4, p<.001). The mean steering change in Groups 3 (3.6°), 4 (5.8°), and 5 (13.8°) was significantly larger than Groups 1 (2.2°) and 2 (3.1°; p<.005 for all comparisons), and the mean change in Group 5 was larger than Group 3 (p=.0036).
- *Highway exit.* 39.8% (129), 50.4% (60), 42.9 (18), 44.0% (11), and 21.4% (3) of the takeovers from Groups 1 to 5 involved passing a link or non-highway road within 1 min after Autopilot disengagement. Starting time of highway exits significantly differed between takeover groups (χ^2=30.5, df=4, p=.001). Compared to Groups 4 (5.2 s) and 5 (0 s; mean 30.1 s), Groups 1 (22.2 s), 2 (15.0 s), 3 (5.2 s) had much longer time from Autopilot disengagement to highway exit (p<.05 for all comparisons). Also, Group 2 was closer to highway exit than Group 1 (p=.003).
- *Upcoming minimal speed (10s~60s).* The upcoming minimal speed was significantly different among the takeover groups (χ^2=109.5, df=4, p<.001). Post hoc tests showed that the upcoming minimal speed was much lower in Groups 2 (22.2 mph), 3 (21.4 mph), 4 (7.6 mph), and Group 5 (8.2 mph) than Group 1 (42.8 mph; p<.001 for all comparisons).

4 DISCUSSION

Driving monitoring systems (DMS) have been implemented in commercialized passenger vehicles equipped with advanced driver assistance systems (ADAS) to detect driver states (e.g., distraction) that have the potential to degrade takeover safety. Understanding the context and associated takeover behaviour is valuable for the continued evolution of DMS such that systems can become more

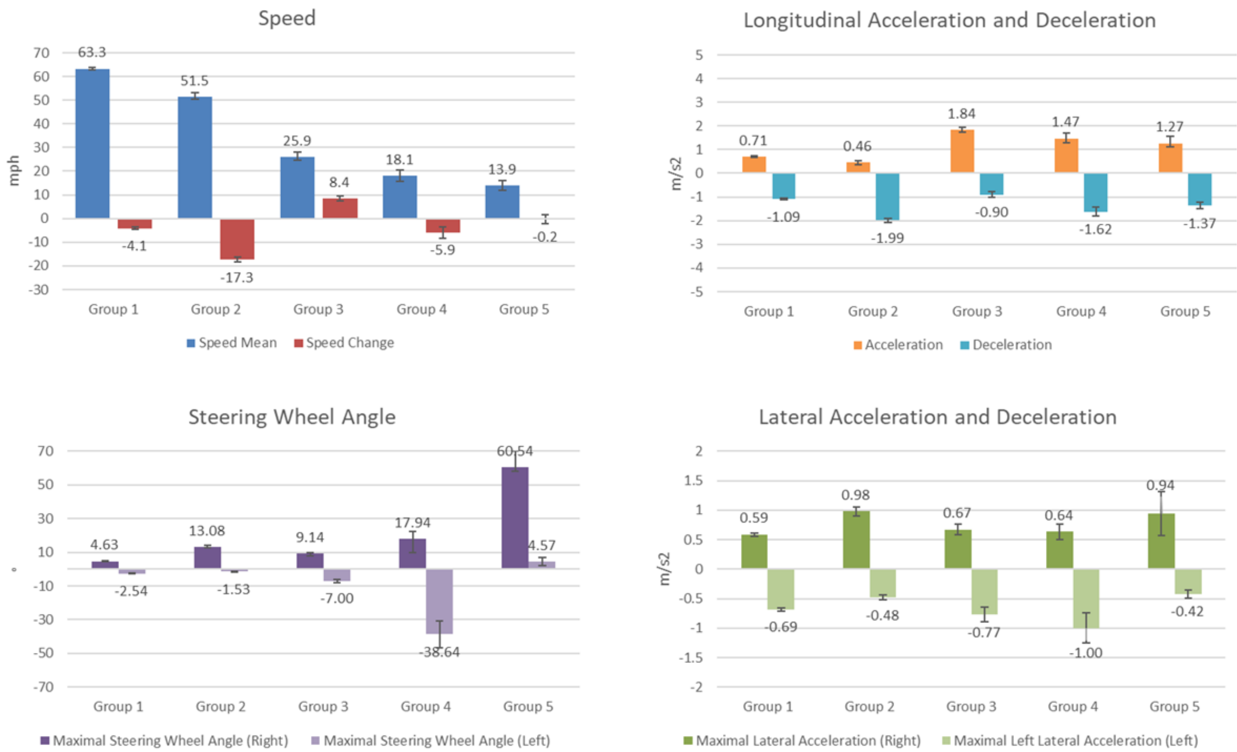

Figure 5: Characteristics of the five categories of AP-related takeovers.

adaptive to real-world dynamic environments and ensuring enhanced safety support and driver experience. To support this goal, the paper presented clustering analysis of takeover events from naturalistic driving involving the use of Cadillac's Super Cruise and Tesla's Autopilot based on vehicle kinematics. Then, contextual factors associated with each takeover category were analysed, providing initial explorations of adaptive driver monitoring approaches.

Takeovers mostly happened on highways and were largely associated with curved roads [29]. Agglomerative hierarchical clustering analysis discovered similarities between SC- and AP-related takeovers (Groups 1–4), suggesting that these takeover patterns may be generalised to the use of other Level 2 ADAS that provide similar functions as Super Cruise and Autopilot. Takeovers in Group 1 occurred at a highway speed without large speed or steering control change, which was the most common takeover related to both systems and called "normal takeover". Takeovers in Group 2 occurred at a similar speed as normal takeover, but with strong deceleration (and speed decrease) and limited steering wheel rotation, indicating a type of "braking takeover". Unlike normal takeover and braking takeovers, takeovers in Groups 3 and 4 only occurred at a lower-than-normal speed. However, Group 3 showed large acceleration while Group 4 showed strong deceleration with large steering rotation, a sign of evasive manoeuvre, so Groups 3 and 4 are called "accelerating takeover" and "evasive-manoeuvre takeover", respectively. Group 5 of AP-related takeovers were featured by very large steering wheel rotation to right (~60°), as "right-swerve takeover". It did not exist for Super Cruise. It is hypothesized that this takeover category did not exist since Super Cruise is geofenced to highways [8], which limits the possibility of car swerve.

How did contextual factors contribute to these takeovers? For both Super Cruise and Autopilot, normal and decelerating takeovers happened in similar pre-takeover contexts: larger headway distance to the lead car (smaller lead-car proximity), small speed change, small deviation from the speed limit, and small steering wheel rotation. But decelerating takeover was partially caused by the need of entering the off ramp in a shorter time window (mean: SC=14.5 s, AP=15.0 s) than normal takeover (mean: SC=30.1 s, AP=22.2 s), so drivers had to decease vehicle speed for upcoming highway exit. If there was no highway exit, decelerating takeover was adopted to prepare for foreseeable slow-driving conditions, sometimes fully stop, often due to upcoming traffic or other less common situations (e.g., observing the flashing light of policy cars parked on the roadside). These contexts reveals that normal and decelerating takeovers are based on strategic or manoeuvre levels of decision making [16].

Accelerating, evasive-manoeuvre, and right-swerve (Autopilot only) takeovers all happened during the operation of Super Cruise or Autopilot in slow and close car following scenarios. More specifically, before the accelerating takeover, Super Cruise imposed larger speed decrease (and smaller steering change) when approaching to the lead car, which may be an "unwanted action" resulting in disengagement [29]. On the other hand, Autopilot performed larger

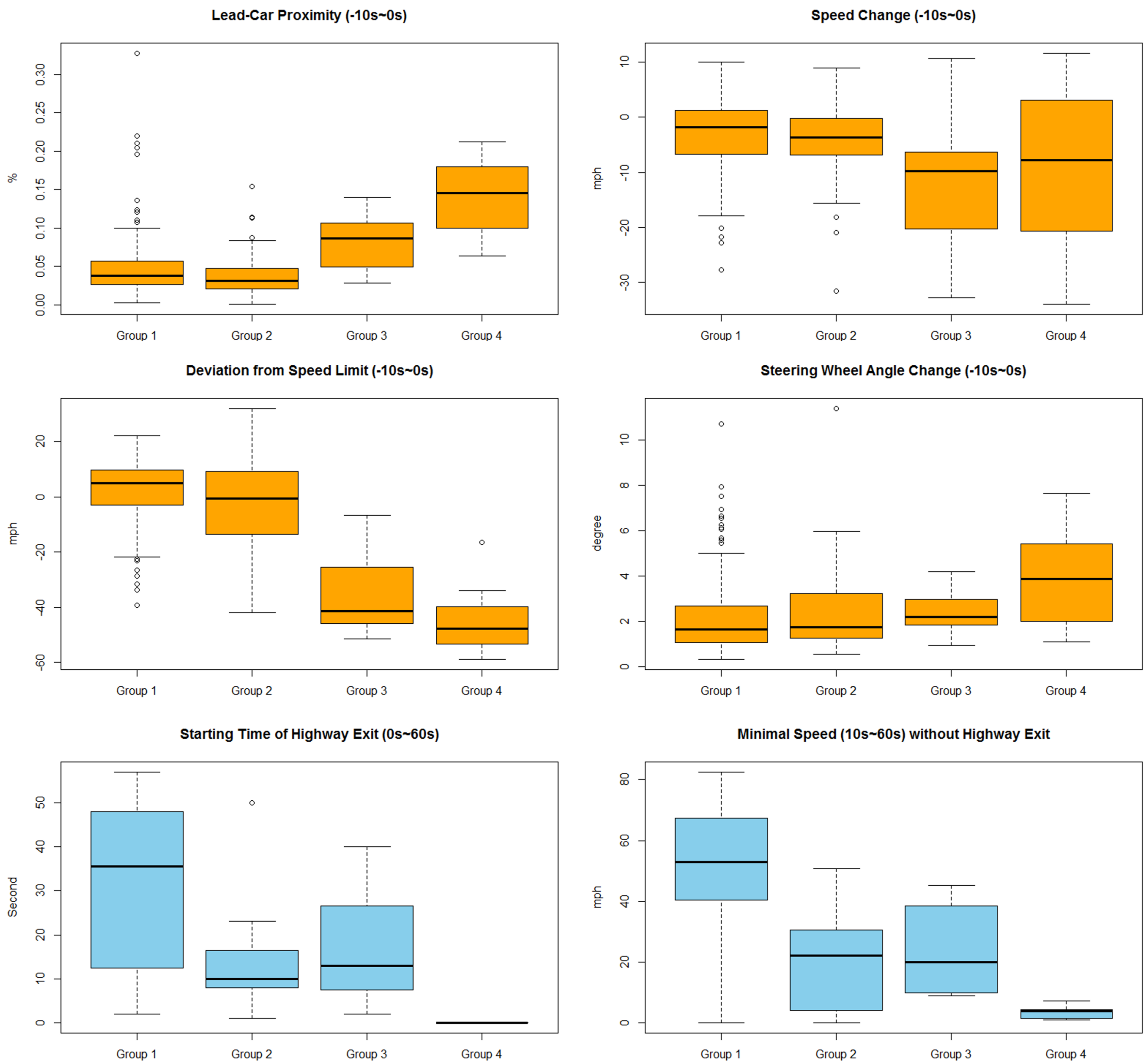

Figure 6: Analysis of contextual factors associated with SC-related takeovers.

steering wheel rotation (instead of speed change) in slow car following prior to disengagement, implying drivers' belief that their manoeuvre was better than Autopilot's in these scenarios.

The analysis of various takeovers and underlying contextual factors can advance the design strategies of DMS for supporting takeover in various scenarios. For example, road curvature, headway, and detected upcoming events may be computationally combined with glance metrics in DMS to calibrate the thresholds of required attention, so that risky attentional states may be detected in the context that takeover is likely to occur. This adaptive driver monitoring concept has been explored in a similar application called AttenD2.0, which is a context-depend multi-buffer driver distraction detection algorithm [2].

4.1 Limitations and Future Research

Demographic features of the participant sample are a key limitation of the data presented, which are comprised of a relatively small and entirely male sample. In order to confirm the generalisability to findings to a broader population, future research should incorporate

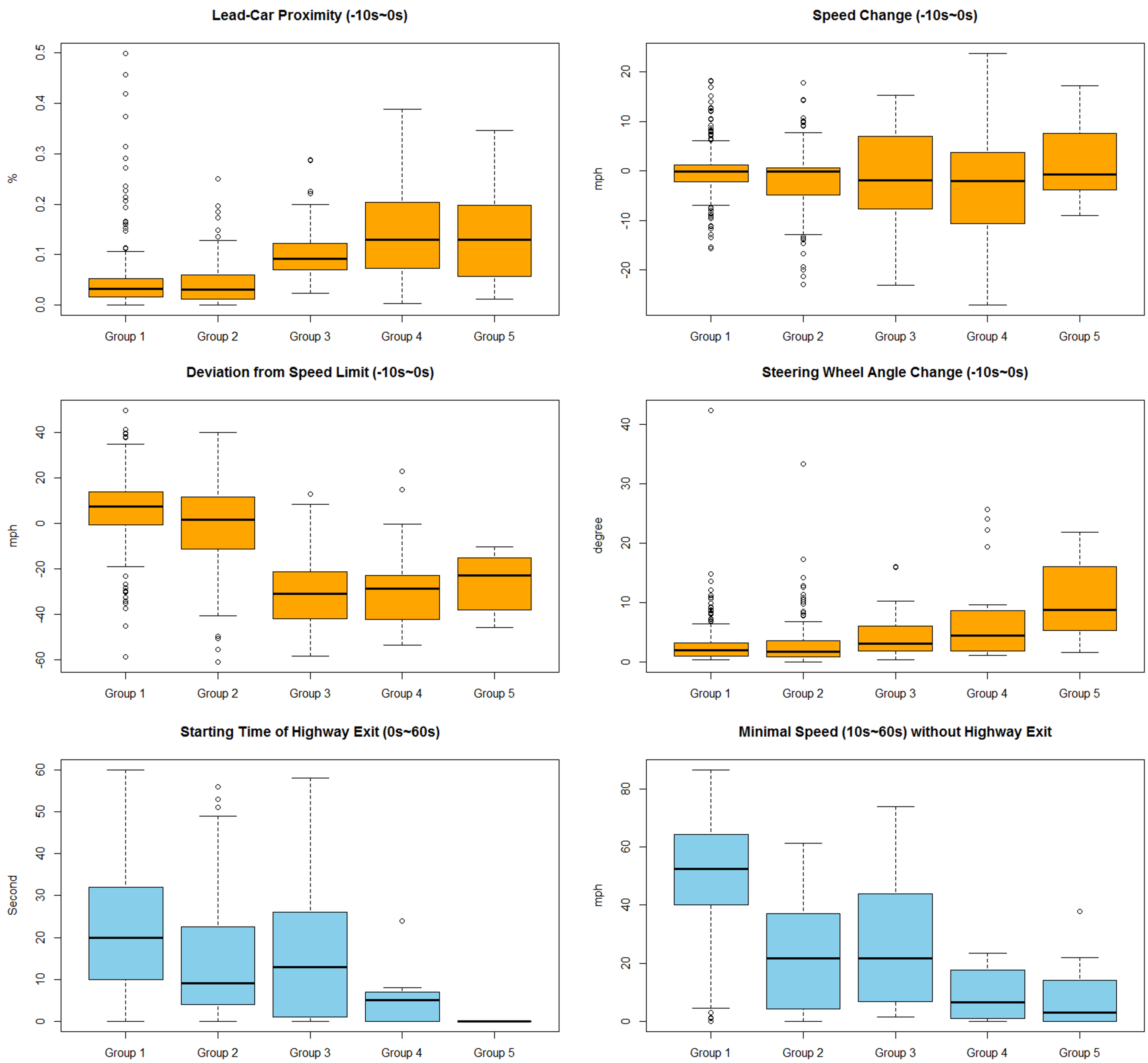

Figure 7: Analysis of contextual factors associated with AP-related takeovers.

a greater diversity of demographic features with a larger overall sample including female drivers. Moreover, takeover behaviour was characterised by high-level features over a certain window (e.g., maximal acceleration and maximal steering wheel angle). Richer behavioural information is contained in original time series of vehicle kinematics. Driving kinematics can be decomposed into a sequence of sub-control events (e.g., steering control being decomposed into a sequence of left and right rotations) using time series segregation and clustering [20, 31]. It is possible that this approach may be more informative for developing reference takeover behavioural models [24]. Also, future research needs to extract more road features, including lane marks, road curvatures, road slopes, splitting roads, and time of day to construct more comprehensive contexts for takeover analysis. Additionally, the precision of lead-vehicle proximity needs to be improved in curves and hills. Finally, future research should ideally incorporate critical and non-critical takeover events, although the former category is inherently more difficult to obtain in naturalistic driving.

5 CONCLUSION

The paper contributes to the first wave of studies of naturalistic takeover and highlights the need for deeper exploration of real-world driving data. Specifically, the paper presented the findings about how contextual factors associated with different types of takeovers using several hundreds of takeover events in the MIT-AVT naturalistic driving study. Hierarchical clustering analysis discovered similar takeover groups between Super Cruise and Autopilot based on vehicle kinematics: normal takeover, braking takeover, accelerating takeover, evasive-manoeuvre takeover, and right-swerve takeover (Autopilot only). Context analysis showed that takeovers happened mostly on highways, some on curved roads. Braking takeover at a normal highway speed was associated with upcoming highway exits or foreseeable low-speed situations, while accelerating, evasive-manoeuvre, and right-swerve takeovers were mostly caused by unwanted ADAS actions in slow car following, such as strong break and large steering. The findings illustrate the plausibility of assessing the contextual features of takeover events for the development of context-based reference models, against which abnormal or unsafe behaviour can be compared and identified in real-time systems. Generating such models and characterising driver response profiles are crucial steps in developing adaptive and responsive DMS and ensuring the safety of increasingly automated driving systems.

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