Using gaze to understand shifts in visual attention during conditional automation with non-driving related tasks

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Understanding drivers' visual scanning strategies is critical for designing safe and effective interfaces for transitions between automated and manual driving modes in conditionally automated vehicles. This paper presents a novel application of Markov Chain analysis to assess how different non-driving related task (NDRT) interfaces influence drivers' attention allocation and gaze transitions in SAE Level 3 automated driving. We present findings from a driving simulator study (N=46) comparing three conditions: baseline (no NDRT), mobile phone NDRT, and head-up display (HUD) NDRT. Our analysis combined Markov Chains of drivers' gaze transition probabilities with gaze dispersion metrics. Results show that while HUDs offer advantages over mobile devices, both NDRT conditions compromise drivers' attention distribution and gaze transitions to safety-critical areas. The Markov Chain approach reveals valuable insights into temporal aspects of attention allocation, informing the design of more effective in-vehicle interfaces. These findings have significant implications for HCI in automated vehicles and may demonstrate the potential of Markov Chain analysis for understanding user behaviour in complex, dynamic HCI environments beyond the automotive context.

CCS Concepts: • **Human-centered computing → User studies**; **Laboratory experiments**; **HCI theory, concepts and models**.

Additional Key Words and Phrases: NDRT, Gaze Behaviour, Automated Vehicles, HMIs, Markov Chains

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1 INTRODUCTION

Introducing vehicle automation technologies in modern vehicles allows the human driver to drive without constantly engaging in the driving task. Consequently, drivers are more likely to attend to non-driving-related tasks [4]. This engagement in non-driving-related tasks—or NDRTs—may compromise drivers' situation awareness [9, 25] and their subsequent capabilities to resume control if a transition is needed [see 5, 23]. This issue is especially critical for current vehicle automation technologies with SAE levels 2/3 capabilities [29]. For these levels, drivers must be able to safely recover control of the driving task if the vehicle cannot deal with its operational design domain (ODD) limitations.

Recent research in the field of driver state monitoring (DSM) systems has suggested that better attention management, e.g., adequately splitting drivers' attentional resources between the driving task and NDRTs, is important for maintaining situation awareness [31, 40] and affects take-over performance during safety-critical scenarios [18, 21, 22, 24, 38]. With that in mind, recent driver state monitoring systems are focused on supporting safe driving, mediating drivers' engagement with NDRTs, by using advanced driver distraction warnings. In recognition of the safety role they play, these systems will be required in European vehicle makers[1] as part of the revised General Safety Regulation and are being proposed to be mandatory in the United States of America[2].

Past findings in the literature support the idea that the effectiveness of attention management strategies in automated vehicles (AVs) may be influenced by the location of the NDRT. For instance, using a driving simulator study, Gerber et al. [11] have compared drivers' frequency of NDRT self-interruptions when engaging in an NDRT presented in a handheld mobile device, with that of a head-up display (HUD). The authors' results suggest that when using the HUD, drivers are more likely to re-focus their attention towards the forward roadway and centre of the road, compared to when using a mobile device. Their results suggest that HUDs may be a promising solution for NDRT presentation. By presenting information on the windshield, HUDs may foster better situation awareness and better attention management as they help direct the driver's visual attention to the forward roadway. These results are supported by [19, 20], who reported that drivers in the same experiment setup had better reaction times to a takeover task, and reported lower levels of workload, when engaging with the NDRT using a HUD, when compared to a mobile phone. Xu et al. [37] have also demonstrated the value of HUDs as an efficient tool for conveying information to the driver in a transition of control scenario, helping them maintain situation awareness.

Despite the potential contribution of HUDs to driver safety in automation, such technology is not without its limitations. For instance, studies in aviation [see 35] have demonstrated that flight pilots using HUDs can suffer from attention tunnelling and impaired perception capabilities compared to those using conventional instrument panel interfaces. Similar issues were reported in the automotive field [28] whereby HUDs may occlude drivers' view of relevant information and tunnel drivers' attention due to the presentation of continuous salient stimuli. Despite advocating in favour of using HUDs for AVs, Pečečnik et al. [32] have warned about the potential increased scenario complexity caused by HUDs, which may compromise drivers' visual scanning capabilities.

[1]Revised General Safety Regulation - Regulation (EU) 2019/2144 of the European Parliament and the Council. https://eur-lex.europa.eu/eli/reg/2019/2144/oj, November 2019. Retrieved: June 2024.
[2]Stay Aware for Everyone (SAFE) act, https://www.congress.gov/bill/117th-congress/senate-bill/1406 April 2021. Retrieved: June 2024.

We argue that the increased visual scenario complexity caused by NDRTs presented in HUDs can compromise drivers' abilities to safely scan the environment. Past studies on this topic [11, 20] have relied on gaze concentration between the road environment and the NDRT to assess drivers' visual attention. While these measures provide insights into the overall pattern of attention distribution, they have limited capabilities in explaining safety-related scanning patterns and attention shifts. Attention shifts are relevant in complex driving scenarios, as they can reveal how quickly and efficiently drivers can re-focus their attention on critical areas of the road when necessary. Thereby, attention shifts can offer additional insights into drivers' scanning behaviour and potential safety implications. Hence, this study aimed to overcome the limitations of previous studies highlighted above by assessing drivers' attention management strategies through the observation of their attention shifts throughout the environment. The Markov Chains approach offers unique and valuable insights into drivers' attention management strategies as it considers the temporal aspects of gaze transitions [see 12, 34].

Previous studies have successfully depicted drivers' hazard perception scanning patterns in both manual driving and vehicle automation, using Markov Chains of gaze transitions between areas of interest [see 12, 34]. Markov Chains are mathematical models that describe a sequence of events or states. In these models, the probability of each event depends only on the state attained in the previous event. In the context of gaze analysis, Markov Chains can be used to model the probability of a driver's gaze transitioning from one area of interest to another based on their current gaze location.

Generic visual attention shift and gaze transition between areas of interest have been used in previous studies to understand drivers' information processing on complex scenarios, such as lane change manoeuvres [6, 7, 30, 33]. However, this approach does not provide contextual information regarding the time and origin of drivers' transition. Previous studies have demonstrated the value of Markov Chain analysis in providing insights into drivers' gaze patterns, attention shifts and attention allocation between different areas of interest. These insights can be linked to safety-relevant behaviours and potential crash incidents [34]. The main advantage of Markov Chains of gaze transitions as a tool to understand drivers' attention management is that it provides context to the drivers' shifts of attention, providing not only information about where the attention is being diverted to but also from where it is being drawn. For example, studies from Gonçalves et al. [12] have shown that during automation, drivers were more likely to perform gaze transitions between two information sources without attending to the road centre, exposing the driver to risks regarding rear-end collisions.

Markov Chains are commonly used as a tool for developing forecasting models in different fields, such as stock market prediction [see 14]. In the field of human behaviour, Markov Chains were successfully introduced in computational models, aiming to describe and replicate human gaze behaviour [see 1–3, 34]. More recent studies were able to use Markov Chains of gaze transitions to understand drivers' interactions with AVs in terms of lane-change manoeuvres [12], situation awareness estimation [31], prediction of takeover reactions [36], and interactions with in-vehicle interfaces [13]. However, its application to understanding drivers' interactions with non-driving-related tasks is largely unexplored.

In light of the research gap mentioned above, this study employed an advanced driving simulator to compare gaze patterns in three different conditions: 1) automated driving without NDRTs (baseline), 2) NDRT using a mobile phone (mobile), and 3) NDRT using a HUD. To better understand drivers' attention management strategies and potential safety implications, we conducted a post-hoc analysis of the data, aiming to address the following research questions: 1) How do drivers' engagement in NDRTs affect their attention distribution and gaze transitions between areas of interest (AoIs)? 2) How does the use of HUD as an HMI for NDRTs influence drivers' visual scanning and attention management strategies? Our approach aimed to extend the application of Markov Chain analysis to answer these questions.

Our contribution relies on the exploration of temporal aspects of drivers' attention management. This is done by observing the frequency of drivers' attention shifts across the environment during extended automated driving periods through the use of Markov Chains. While techniques like gaze dispersion and concentration analysis provide an overall picture of where drivers' attention is being focused, our approach using Markov Chain analysis provides a more nuanced understanding regarding the attention management strategies used to achieve such focus. In other words, it allows us to quantify the probabilities of transitioning between different areas of interest in drivers' gaze patterns. Our findings have the potential to significantly impact future interface design for AVs and other complex systems where attention management is critical, by providing empirical evidence on how different interface designs affect users' attention allocation and gaze patterns.

Beyond the automotive context, this research contributes to the broader field of HCI by demonstrating how attention management can be analysed and understood in complex, multi-task environments. This work aligns with core HCI principles of designing interfaces that support optimal user performance and safety, particularly in scenarios where attention must be divided between multiple tasks or information sources. The methodology and insights presented here may inform the design of interfaces in other domains where users must balance attention between a primary task and secondary activities, such as in aviation, industrial control rooms, or even everyday multi-tasking scenarios with mobile devices.

2 METHODOLOGY

We used an existing driving simulator study as an example to showcase the application and utility of Markov Chain analysis in understanding drivers' attention management strategies in conditionally AVs with NDRTs—in particular, insights into the temporal aspects of drivers' attention allocation and the potential to inform the future design of AVs interfaces. Below, we first describe the simulator study for context, followed by a description of the Markov Chain analysis.

2.1 Simulator Study

The dataset underlying the Markov Chain analysis is representative of other conditionally automated driving simulator studies, including a driving simulator with eye-tracking hardware with a range of defined areas of interest (AoIs), NDRTs (in this case, watching videos on different display modes: mobile phone vs. head-up display and baseline) and a driving scenario with automated driving and a take-over request (TOR).

2.1.1 Experiment Apparatus. The study was conducted using an Advanced Driving Simulator. It features a real-vehicle cabin with automatic transmission. The driving simulator is equipped with a surround-sound system that replicates engine and environmental noise. Also, a six-degree-of-freedom motion platform provides the vehicle with movement in three dimensions (see Figure 1). Three front-view projection screens (later defined as "Centre Screen", "Left Screen", and "Right Screen") provide a 180-degree high-resolution field of view for the driver, LCD monitors are used as the lateral and rear-view mirrors to simulate side and rear-view images (later defined as "Right Mirror", "Left Mirror", "Rear Mirror").

To collect drivers' eye-movement data during the experiment, Seeing Machines' PC-DMS3 (PCDMS) eye-tracking device was employed. The PCDMS uses a sensor bar installed on the vehicle's dashboard above the steering wheel to minimise occlusion. The sensor bar features an infrared camera embedded in the centre and a pair of pulsed infrared lights on either side. This setup enables the PCDMS to monitor drivers' head and eye movements effectively.

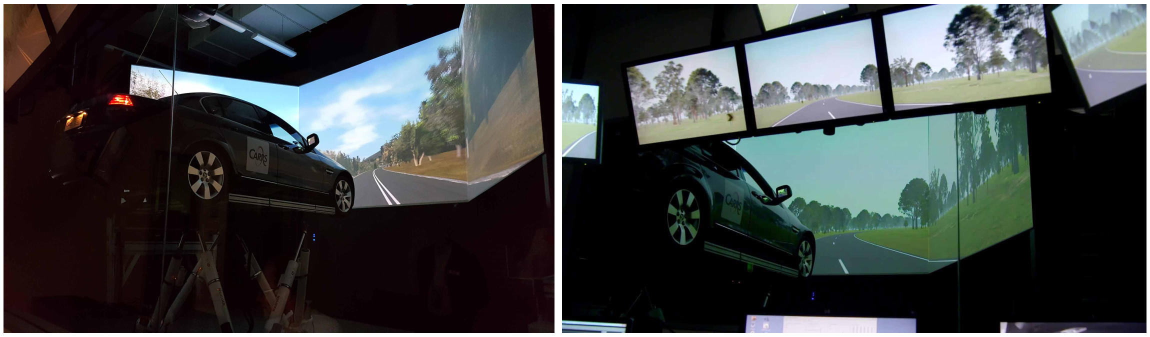

Fig. 1. Advanced Driving Simulator.

This study focused on the drivers' eye-gaze dispersion during the automated drive stage and did not consider the period after the TOR was issued. Head/eye-gaze tracking data were collected–at a sample rate of 46 Hz–for the automated drive length, which was around 13 minutes. The recorded videos and data are then processed by Seeing Machines' proprietary algorithms, which generate detailed head and eye-movement measurements such as gaze data. The extracted measurements included a) gaze yaw, b) gaze pitch, and c) the intersection of drivers' gaze with different AoIs.

For this study, we defined 10 AoIs (see Figure 2), namely "Centre Screen", "Left Screen", "Right Screen", "Navigation", "Rear Mirror", "Left Mirror", "Right Mirror", "Centre Console", "Instrument Panel" and "Unknown". The "Unknown" AoI refers to any gaze fixations that do not fall within the boundaries of the other defined AoIs, representing moments when the drivers' gaze is directed towards areas not captured by the specific AoIs. It is relevant to note that when the driver's gaze is located in the "Unknown" AoI, they may not be attending to important driving-related information, such as the road ahead (i.e., "Centre Screen" AoI), mirrors, or instrument panel, which could potentially impact their situation awareness.

To create the driving scenarios for this study, real-world recorded videos were collected and then played back to simulate automated driving in the simulator (building on [10, 16]). To record the videos, a car was manually driven along one of the most recognisable routes in the city, and the ambient driving scene was recorded by cameras set up on the vehicle. The driver aimed to mimic the performance of an AV by adhering to speed limits, maintaining passive following distances, and employing highly anticipatory lane selections. Multiple trips were recorded, and three similar but different trips were selected for the study. Each trip lasted approximately 15 minutes and followed the same route, which included inner-city roads (approximately 5 minutes), a major motorway (approximately 8 minutes), and suburban roads (approximately 2 minutes). A simulated planned TOR was issued at the exit of the motorway in all three scenarios. All trips were conducted during the same time of day to ensure similar traffic density.

2.1.2 Participants. The study recruited 49 participants, but only 46 (23 males and 23 females) completed the experiments with full head/eye-gaze tracking data records. The participants, aged between 20 and 62 years old, had a mean age of 32.3 years (standard deviation of 8.7 years). Participants were recruited from local communities through social media posts, university website advertisements, and snowball sampling. Inclusion criteria required participants to be over 18 years old, hold a valid driver's licence, and be able to attend a 2-hour study session. Exclusion criteria included medical conditions affecting driving, history of epilepsy or motion sickness, pre-existing neck or back injuries, migraine history,

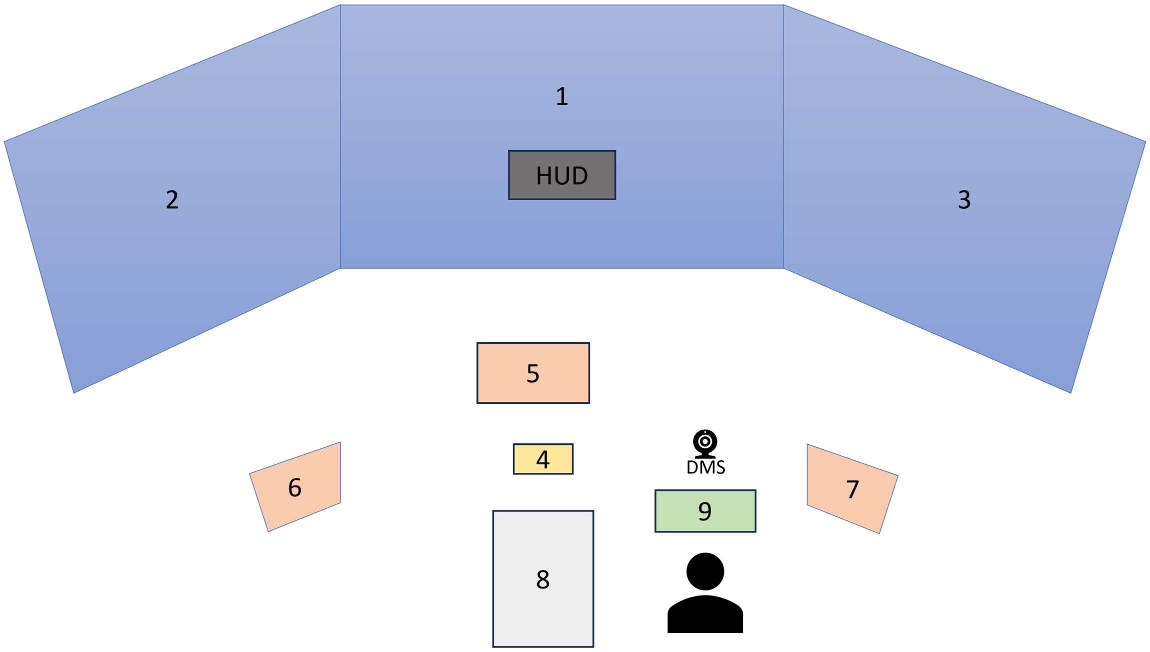

Fig. 2. Areas of Interest: 1) "Centre Screen", 2) "Left Screen", 3) "Right Screen", 4) "Navigation", 5) "Rear Mirror", 6) "Left Mirror", 7) "Right Mirror", 8) "Centre Console", 9) "Instrument Panel", and "Unknown".

pregnancy, and COVID-19 risk factors. All participants were screened for these criteria before being included in the study.

2.1.3 Study Design. The study employed a within-subject design in which all participants underwent three drives in an SAE Level 3 AV [29] simulator. Each drive, which was counterbalanced across the scenarios, included a planned TOR when exiting the highway on the same route and one of three counter-balanced NDRT engagement conditions: watching a video on a mobile phone, watching a video on a head-up display, and a baseline condition with no video. Drivers were allowed to position the mobile phone at any position they felt comfortable—even outside of their field of view from the driving scene. The HUD condition simulated a head-up display by overlaying a 61.5% transparent image (76cm x 43cm) onto the front projection screen (partially occluding the driving scene), positioned approximately 3.75 meters from the driver's eye. Figure 3 displays the mobile and HUD conditions. The rationale behind the HUD implementation is based on the possibility for drivers to engage in NDRTs while keeping relative vigilance of the driving environment. To mirror real-world driving scenarios, participants were given the freedom to select their preferred TV show, encouraging voluntary and natural engagement with the content. The video began playing as soon as the automation was engaged and remained displayed throughout the entire automated phase. Participants were told to engage with the video as they normally would during an automated drive while remaining aware that they might need to take over control at some point. No instruction was provided regarding how or when drivers should interact with the NDRT. Therefore, drivers were free to mediate their attention split between the NDRT and the road environment at their own discretion. Lastly, a planned TOR was issued towards the end of the driving route when the vehicle exited the motorway.

(a) (b)

Fig. 3. NDRT display modes: (a) Mobile condition, showing participant watching video on their handheld device, and (b) HUD condition, where the HUD to watch the video is projected with 61.75% transparency on the centre screen.

2.1.4 Experiment Procedure. Participants arrived at the simulator, and after a detailed introduction, they signed a consent form. Participants were informed that their participation was voluntary, and the collected data would remain anonymous and be reported in an aggregate manner only. They were introduced to the experiment procedure, including the capabilities of the simulated AV, the NDRT, the TOR, and the "shadow" driving. "Shadow" driving refers to a technique where participants manually replicate the car's longitudinal and lateral movements as presented by the recorded videos. This involves physically manipulating the steering wheel and pedals in real-time as if they were actually driving the car, even though they are not in control of the vehicle. The TOR was presented through both auditory and visual alerts, requiring participants to take over control of the vehicle (i.e., shadow drive) when prompted. Each participant also chose two episodes from their favourite TV show to watch during two of their automated drives, which served as the NDRT. The selected TV shows varied across participants–as they were able to choose what they liked. This approach aimed to ensure that the NDRTs were engaging and representative of the participants' typical viewing preferences, thus providing a realistic level of cognitive engagement during the automated drives.

Following the preparation, all participants completed an approximately five-minute familiarisation drive in the simulator. During this familiarisation drive, they experienced the process of automated driving, where they were required to engage in the NDRT (watching the TV show). Participants also experienced the TOR event, which prompted them to disengage from the NDRT and prepare to take over control of the vehicle. As the driving scenarios were recorded videos, participants did not take over control of the vehicle but were instead asked to shadow drive. They were advised to shadow drive until they were comfortable with the concept.

After agreeing to proceed with the study, participants took part in three distinct drives in a randomised and counterbalanced order, each including a TOR event. The eye-tracking data collected and analysed in this study focused on the automated driving period before the TOR event. As soon as the TOR event was initiated, participants were directed to perform "shadow" driving for the remaining two minutes until the end of the scenario. This ensured that participants maintained their attention on the road during the transition of control, even though they were not actually controlling the vehicle. All participants were exposed to identical conditions, allowing for a direct comparison between the different scenarios [11, for further details, please see 19]. Each drive was followed by a motion sickness questionnaire to assess their suitability to continue the experiment.

The entire experiment, including interruptions to reset and brief breaks in between, took about 1 hour. After completing the experiment, each participant received a $70 gift voucher as compensation for their participation. The study was conducted in accordance with the national ethics code where the study took place and approved by the university's ethics review board (approval number 1700000425).

2.2 Markov Chain Analysis

Our comprehensive analysis of driver gaze behaviour under three distinct conditions—Baseline, Mobile, and HUD—used a multifaceted approach to examine how each interface affects attention management and gaze scanning strategies during the automated drive. Prior to the analysis, the collected gaze data were filtered and validated to ensure that the "Unknown" AoI represented gaze fixations outside the predefined AoIs and did not include any missing data. The primary method employed in this analysis was Markov Chain analysis, which was used to model and understand drivers' gaze transitions between different AoIs.

Markov Chain analysis is a mathematical method for modelling sequences of events where the probability of each event depends only on the state of the previous event [26]. It involves a finite set of possible states within a system and the transitions between these states (see Figure 4). The likelihood of moving from one state to another is represented by transition probabilities, typically organised in a matrix. Markov Chain analysis is used to analyse systems that transition between discrete states over time, allowing for predictions of future states based on current conditions. The Markov Chain transition probability is given in Equation (1).

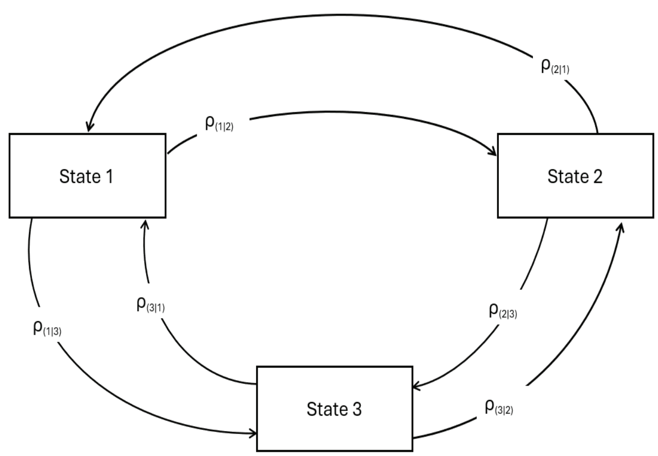

Fig. 4. Three-state Markov Chain model with transition probabilities.

$$P(X_{n+1} = j | X_n = i) = p_{ij} \tag{1}$$

The Markov Chain analysis generated transition matrices (Equation (2)) for each participant, containing the probabilities of transitions between AoIs. These matrices were used to compare the gaze transition probabilities across conditions. By applying Markov Chain analysis to drivers' gaze transitions, we aimed to gain insights into their attention allocation and scanning patterns under different NDRT conditions. To complement our analysis, Markov Chains (i.e. gaze transition matrices) were used in parallel with drivers' vertical/horizontal gaze dispersion.

$$P = \begin{pmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{pmatrix} \tag{2}$$

Fixations were calculated as a point of permanence of drivers' gaze exceeding a minimum of 150 ms under a distance threshold of a 1-degree radius. The technique and thresholds for fixation detection are in line with standard protocols used in the field [30] and consistent with other studies in the field of gaze behaviour in automated driving [12, 22]. Gaze dispersion was calculated as the standard deviation of drivers' gaze positions throughout their automated driving periods. To complement and further understand the fixations and gaze dispersion data, we employed scatter and kernel density estimate (KDE) plots of gaze points distributed across the different AoIs. KDE plots provided a graphical representation of fixation densities across the vehicle's dashboard and the road ahead, revealing distinct visual attention patterns for each condition.

Diverse statistical tests were used to compare differences in drivers' gaze behaviour between the experimental conditions. Kolmogorov-Smirnov tests were used to assess the dataset's normality. For cases where normality was assumed, parametric statistical tests were conducted using ANOVA tests. Since the gaze transition probabilities generated by the Markov Chains failed the normality tests, non-parametric Wilcoxon's tests were used for statistical evaluation. An alpha value of 0.05 (95%) was used for all tests to assess the statistical significance. Individual comparisons between scenario conditions were evaluated by Bonferroni post-hoc tests. For the cases where non-parametric tests were applied, sample-paired Mann-Whitney U tests were used as post-hoc tests.

3 RESULTS

From an HCI standpoint, these results highlight how different interface designs (mobile, HUD, and baseline) significantly impact drivers' attention allocation and strategies. The Markov Chain analysis reveals not just where users look, but how they transition between different areas of interest, providing valuable insights into the cognitive processes underlying their interactions with the NDRTs while the automated driving system is engaged.

3.1 Gaze Dispersion

Two 3X1 repeated measures one-way ANOVAs were conducted to measure the effect of the experimental conditions (baseline, HUD, mobile) on drivers' vertical and horizontal gaze dispersion. The ANOVA results (see Figure 5) showed a significant effect of the experimental conditions on drivers' vertical gaze dispersion [F (2, 137) = 127.21, p > 0.001, ηp^2 = 0.635]. Post-hoc Bonferroni tests revealed that drivers in the mobile condition presented a significantly higher average vertical gaze dispersion (M = 10.913°, SD 3.070°) than the baseline condition (M = 6.148°, SD= 1.765°), which was significantly higher than in the HUD condition (M=3.912°, SD=1.213°).

The ANOVA results on drivers' horizontal gaze dispersion (see Figure 5) showed a significant effect of experimental conditions [F (2, 137) = 31.943, p > 0.001, ηp^2 = 0.321], where Bonferroni post-hoc tests showed that the baseline condition presented the highest gaze dispersion (M = 18.550°, SD=5.376°), followed by the mobile condition (M=15.136°, SD=6.170°), with the lowest values seen for the HUD (M=9.628°, SD=4.585°).

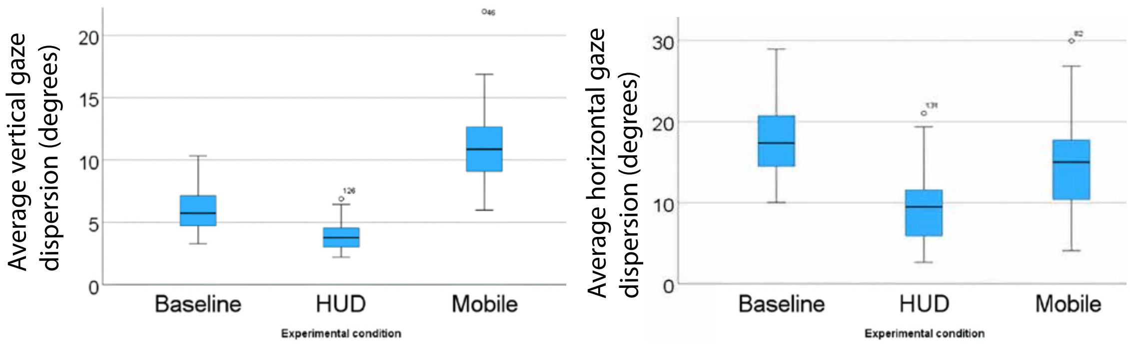

Fig. 5. Average vertical (left) and horizontal (right) gaze dispersion for the three conditions.

Qualitative observation of the KDE gaze plots (see Figure 6) supports the ANOVA results, showing that drivers' gaze seems to be evenly distributed across the driving environment in the baseline condition while constrained to the centre screen for the HUD condition. Regarding the mobile condition, drivers' gaze did not deviate too much on the horizontal plane but presented a high vertical dispersion, which can be explained by the interaction with their handheld device.

Subsequent video analysis showed that the majority of drivers positioned their phones in locations that diverted their gaze from the road: approximately 71% placed this near the steering wheel, while 28% placed it on their lap (see Figure 7). Less than 1% of drivers placed the mobile in other locations, such as the instrument panel or below the centre console. In all of the above cases, the mobile device location would be classified inside the "Unknown" AoI, according to the PCDMS world model.

3.2 Gaze Fixations Transitions

To better represent the distribution of gaze transition probabilities for each condition, aggregated transition matrices (see Figure 8) provided average values for each transition probability between all participants. To analyse the differences between the transition probabilities, multiple Wilcoxon tests were performed. These measured the effect of the experimental conditions on the probability for each individual gaze fixation transition between AoIs to occur over the course of the automated drive. The results of the Wilcoxon tests are reported in Table 1. For better visualisation, the statistical tests were restricted to gaze transitions with an average probability of occurrence above 5% (0.05). Also, only the statistically significant test results are reported in Table 1.

Results showed that drivers generally have a lower probability of transiting their gaze towards the "Centre Screen" AoI in the mobile condition. For instance, drivers in the mobile condition presented an average 37.9% chance of shifting their gaze back to the centre screen when looking towards the navigation system, while the baseline and HUD conditions presented a 69.8% and 54.4% chance, respectively. Similar differences were found in transitions from the left screen, rear mirror, right mirror and right screen towards the centre. Drivers in the mobile condition were also more likely to perform gaze transitions towards the "Unknown" AoI. For instance, drivers in this condition presented a 66% chance of transitioning their gaze towards "Unknown" from the centre screen, while the baseline and HUD conditions presented a 27.5% and 47.2% chance, respectively. Also, drivers in the mobile condition presented a 37.8% chance of shifting their gaze towards "Unknown", while baseline and HUD conditions presented a 20% and 9.5% chance, respectively. As a

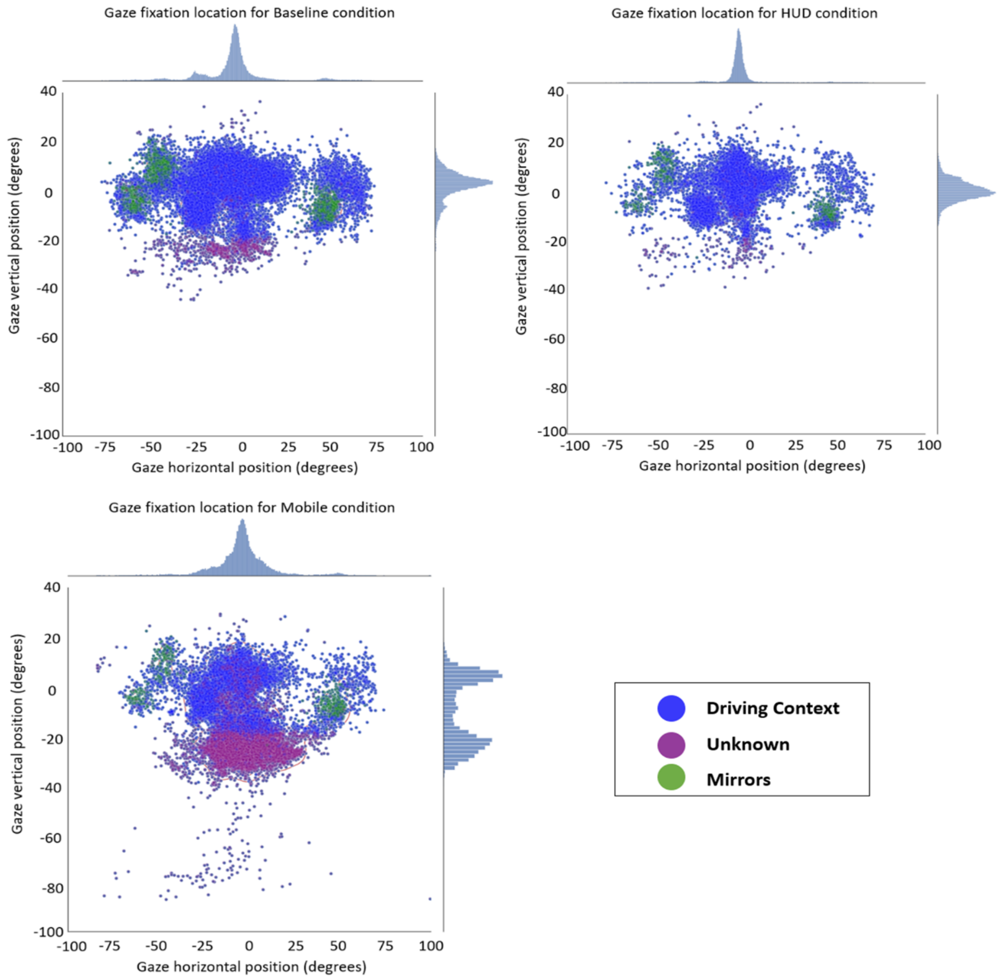

Fig. 6. KDE gaze plots, baseline (top left), HUD (top right), and mobile (bottom).

consequence, the probability of gaze transitions from the centre screen towards the other AoIs in the mobile condition was significantly lower when compared to the other two conditions.

Drivers in HUD and baseline conditions had similar proportions of gaze transitions towards the centre screen. Examples can be found on gaze shifts from the navigation system (baseline= 69.8%, HUD= 54.5%), "Unknown" (baseline= 81.9%, HUD= 88.1%), instruments panel (baseline= 68.7%, HUD= 60.3%), left screen (baseline= 66.2%, HUD= 66.3%), rear mirror (baseline= 65.6%, HUD= 58.8%), right mirror (baseline= 64.4%, HUD= 55.3%), and right screen (baseline= 73.1%, HUD= 60.4%) AoIs. However, drivers in the HUD condition were more likely to transition their gaze from the "Centre Screen" to the "Unknown" AoI (baseline= 27.5%, HUD= 47.2%). Drivers on the baseline had a significantly higher proportion of gaze fixation transitions when it comes to gazes from the centre screen to either the left screen (baseline= 16.1%, HUD= 8.9%) or the right screen (baseline= 18.6%, HUD= 9.7%), and a non-significant trend of slightly

Fig. 7. Examples of smartphone positioning by participants in the mobile condition: Near the steering wheel (top) and on their lap (bottom).

Table 1. Wilcoxon Tests

ORIGIN	Navigation	Unknown	Centre Screen					Instruments Panel		Left Screen	Rear Mirror	Right Mirror	Right Screen
DESTINATION	Centre Screen	Centre Screen	Unknown	Left Screen	Rear Mirror	Right Mirror	Right Screen	Unknown	Centre Screen	Centre Screen	Centre Screen	Centre Screen	Centre Screen
N	132	132	132	132	132	132	132	132	132	132	132	132	132
Combined Median	0.725	0.857	0.4365	0.075	0.029	0.041	0.08	0.138	0.667	0.6325	0.581	0.571	0.698
Mean Baseline	0.69823	0.81932	0.27507	0.16082	0.11398	0.09407	0.18584	0.20198	0.68673	0.66211	0.656	0.64402	0.73132
Mean HUD	0.54525	0.88123	0.47239	0.0885	0.08527	0.07507	0.09655	0.09545	0.60343	0.66336	0.58759	0.5532	0.60384
Mean Mobile	0.37866	0.75227	0.66014	0.04914	0.04914	0.01402	0.03498	0.37827	0.46018	0.36375	0.32395	0.32118	0.42002
Chi-Square	16.545	24.43	40.909	32.909	26.727	10.972	30.977	26.727	12.13	20.364	13.636	19.701	16.545
df	2	2	2	2	2	2	2	2	2	2	2	2	2
Sig.	>0.001	>0.001	>0.001	>0.001	>0.001	0.004	>0.001	>0.001	0.002	>0.001	0.001	>0.001	>0.001

* note that only the significant results are being reported
*note that only transitions with the combined mean higher than 5% (0.05) of occurrence was reported

bigger probability of gaze transition from the centre screen to both the left mirror (baseline= 11.4%, HUD= 8.5%) and the right mirror (baseline= 9.4%, HUD= 7.5%).

4 DISCUSSION

This study assessed drivers' visual attention in an SAE level 3 vehicle automation environment under three different conditions: 1) baseline (no NDRT), 2) a HUD NDRT, and 3) a mobile NDRT. The gaze dispersion analysis showed that both conditions containing NDRTs reduced drivers' lateral scanning and functional field of view. This can be explained by the fact that drivers might be focusing on the NDRT itself instead of scanning the environment. When comparing the two NDRT conditions, results showed that drivers in the mobile condition were more likely to have a higher dispersion

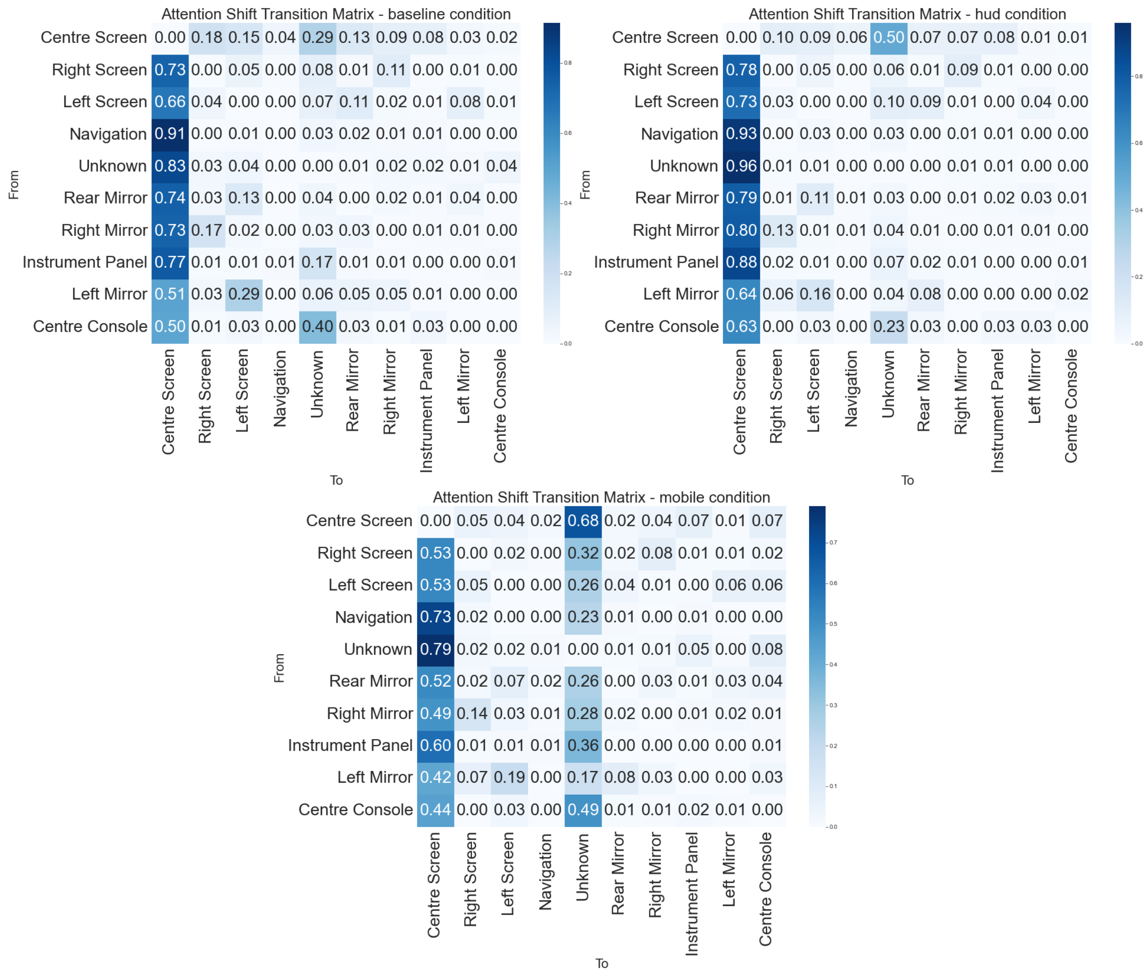

Fig. 8. Aggregated transition matrices: average gaze transition probability for all participants per condition, baseline (top), HUD (middle) and mobile (bottom).

of their vertical gaze. The KDE gaze plots and video analysis confirmed that most of this vertical dispersion was based on gaze to the bottom area of their field of view (e.g., close to the steering wheel or their laps; see Figure 7) and away from the road. Overall, analysis of the gaze metrics, taking into account the position of the HUD and the mobile device, confirmed that participants actively engaged in the NRDTs during the automation period. The HUD condition, by presenting the NDRT information close to the driver's line of sight, allowed drivers to maintain their gaze close to the road environment compared to the mobile conditions. This finding suggests that the HUD condition can partially compensate for the detriments of the NDRT, by reducing the need for large gaze deviations away from the driving context, in line with results from Li et al. [20].

The Markov Chains analysis revealed that drivers in the mobile condition had a higher probability of shifting their gaze to the "Unknown" AoI. This finding, combined with the location of the mobile device far away from the driving environment (see Figure 7), indicates that drivers frequently shifted their attention to their phones. It is important to note that, as part of the study design, drivers were allowed to place their phones in any position they felt comfortable. As a result, participants in the mobile condition were less likely to return their gaze towards the "Centre Screen" after fixating on any AoI not related to the road environment (e.g. "Unknown" or "Centre Console") when compared to the other two conditions.

The results suggest that handheld mobile NDRT increases variability in drivers' attention shifts, potentially compromising the occurrence of relevant gaze transitions for hazard perception. This detriment in drivers' gaze behaviour may affect their capabilities to detect safety-relevant events, exposing them to potential automation failures and reducing their take-over readiness due to reduced situation awareness [8, 22, 39]. This result is similar to findings on visual distraction caused by mobile phones in manual driving [15, 17, 27]. This research contributes to this field by suggesting that drivers' attention management is compromised by mobile devices, even in an automated drive scenario, where they are not manually engaging with the driving task.

The Markov Chains analysis has also shown that drivers in the HUD condition had a similar probability of shifting their gaze towards the "Centre Screen" after fixating on other AoIs compared to the baseline condition. This finding, together with the KDE gaze plots and ANOVA results on gaze dispersion, suggests that drivers' gaze fixations to the forward roadway were more prominent in the HUD condition, surpassing even the baseline. Generally, a higher percentage of gaze towards the centre area is associated with higher situation awareness [39]. However, the Markov Chains analysis also showed that drivers in the HUD condition were less likely to perform eventual checks on driver-safety-relevant areas of interest, such as the side mirrors or their side lanes, compared to the baseline condition. Furthermore, the Markov Chain analysis showed that drivers in the HUD condition have a higher probability of deviating their gaze from the centre region to the "Unknown" areas. This observation suggests that, despite focusing their gaze towards the road environment—generally associated with improved situation awareness—drivers in the HUD condition had compromised scanning and hazard perception abilities. The contextual information about the location of their gaze deviation—not to driving-related areas, but rather away from the road environment—suggests a potential disassociation between visual focus and cognitive attention. This result aligns with studies from Schnebelen et al. [31], which also used Markov Chains to infer that attentive drivers in automated driving scenarios are characterised by their attention to the road centre and by the likelihood to deviate their gaze to driving-relevant areas of interest, such as side mirrors or the speedometer. Thus, the contextual information provided by the Markov Chains analysis offers a more nuanced tool for inferring the driver state in AVs, extending beyond traditional gaze concentration metrics.

Our findings both align with and extend previous research on NDRTs in AV studies. Consistent with Gerber et al. [11] and Li et al. [19], we found that HUDs increase the probability for drivers to gaze towards the road centre compared to mobile devices. However, our Markov Chain analysis reveals that HUDs may still compromise their hazard perception routine, a nuance not captured in previous studies, as in the example provided above. This may extend Li et al.'s [20] findings on take-over performance, suggesting limitations of HUDs. Our approach quantifies the increased variability in attention shifts with mobile devices, providing a more comprehensive view of attention allocation over time. These insights demonstrate the value of Markov Chain analysis in understanding the complexities of driver attention management in AVs, offering a more detailed picture than traditional gaze metrics used in previous studies.

The results further suggest that although the HUD condition seems to provide benefits over a handheld mobile device by keeping drivers' gaze closer to the forward roadway, this solution still compromises drivers' attention management by reducing their likelihood of checking potentially safety-relevant areas. The HUD condition may lead to a narrower attentional focus on the NDRT, limiting drivers' ability to scan the driving environment effectively. One should note that the use of HUD displays may also increase the chances for drivers to suffer from change blindness or attention tunnelling [35], suggesting that even though drivers might be looking ahead, their attention might not be focused on the road.

The insights gained from the Markov Chains analysis complement and extend the findings from the other analyses. These insights provide a more comprehensive understanding of how NDRTs affect drivers' attention management in AVs. By considering the temporal aspects of gaze transitions, the Markov Chains approach offers unique and valuable insights into drivers' attention management strategies [see 12, 34]. For example, as can be seen in the finding described above, the Markov Chains analysis revealed that drivers engaging in NDRTs are less likely to perform hazard perception-related scans (as suggested by [34]) on the environment. The identification of proportions and probabilities of gaze transitions between different areas of interest provides a nuanced and *interpretable* understanding of drivers' gaze behaviour and how drivers allocate their attention over time. This interpretability is particularly valuable in the context of studying drivers' attention management, as it can help identify specific patterns and strategies that may not be easily discernible using other methods (e.g. gaze dispersion and concentration analysis). These insights about patterns may inform the future design of safer and more effective in-vehicle interfaces and NDRTs. For example, the identified gaze transition patterns could guide the placement of critical information on the HUD to minimise disruptions to drivers' attention and ensure that relevant information is easily accessible when needed. HUDs will need additional HMI design elements focused on managing driver attention with the aim of intermittently interrupting NDRT attention and dispersing their gaze, including other potentially safety-relevant AoIs. Thus, this approach underscores the importance of considering attention management when developing in-vehicle interfaces for conditionally AVs and can inform the design of safer and more effective NDRTs.

5 CONCLUSION AND FUTURE WORK

The results presented above showed increased gaze dispersion for the mobile condition and decreased dispersion for the HUD condition compared to baseline. Markov Chain analysis revealed that drivers using mobile devices were less likely to return their gaze to the road centre. While the HUD condition maintained similar probabilities of on-road glances to baseline, it significantly reduced the likelihood of safety-related visual checks, such as from the road centre to side mirrors and lanes.

Markov Chain analysis of gaze transitions offers a promising approach to understanding drivers' attention allocation and informing the design of safer in-vehicle interfaces. This approach provides a nuanced and interpretable understanding of drivers' gaze behaviour and attention management strategies by identifying the proportions and probabilities of gaze transitions between different areas of interest.

The results of the analysis support the potential benefits of HUD devices over handheld mobile phones for NDRT presentation. Drivers using HUDs demonstrated a higher probability of maintaining their gaze closer to the road centre, potentially reducing the risk of missing critical events. This suggests that handheld mobile devices may present road safety issues even in vehicle conditional automation scenarios. However, our research also highlights that HUDs, despite their benefits, may still impair drivers' ability to scan the environment efficiently.

Our findings emphasise the importance of carefully designing in-vehicle interfaces and NDRT interactions to minimise potential negative impacts on drivers' attention allocation and hazard perception capabilities. The insights gained from applying Markov Chain analysis to drivers' gaze transitions may inform the development of adaptive, user-centred, and context-aware interfaces that promote safer and more effective human-vehicle interaction in the era of automated driving. Furthermore, they highlight the need for further research to test, identify, and validate novel optimal solutions for drivers' interactions with NDRTs, minimising their detrimental effects on drivers' readiness in AVs.

In relation to the optimal solutions, we provide the following considerations: 1) The findings of this study raise the question of where the NDRTs should be positioned to minimise their potential safety impact. Therefore, the position and size (and potentially depth) of displays presenting NDRTs need to be optimised with regard to allowing users to seamlessly switch between the dual-task of a) monitoring the AV and b) the NDRT. 2) Furthermore, our findings suggest that additional HMI design strategies are needed for HUDs, which need to better manage driver attention, dispersing their gaze more towards potentially safety-relevant AoIs during automation. Therefore, 3) The integration of driver monitoring systems (DMS) with HMIs may help keep drivers safe and guide their interactions with NDRTs. For instance, the DMS could inform HMI interventions based on the specific placement of the NDRT and adapt NDRT permissions based on the driver's gaze patterns, such as reducing access to NDRTs if the driver's gaze is excessively focused on the display.

DMS can play a crucial role in mediating safe NDRT engagement by monitoring drivers' gaze patterns and providing real-time feedback or interventions when necessary. For example, if the system detects that a driver does not exhibit gaze transition patterns associated with fall-back readiness, it could prompt the driver to redirect their attention to the driving environment through visual or auditory alerts. This could help prevent prolonged disengagement from the road environment and maintain a minimum level of situation awareness. Furthermore, the measurements provided by the DMS may be utilised in HMI design strategies to support interventions based on the specific placement of the NDRT. For handheld mobile devices, where the driver can face away from the DMS cameras, the DMS could be more proactive in reminding drivers to keep their devices in a position that minimises the need for excessive downward gaze shifts (as shown by participants in our study), reducing the time spent looking away from the road. In the case of HUDs, the DMS may monitor drivers' gaze and nudge them to periodically scan critical areas of the driving environment to avoid excessive focus on the NDRT.

It is relevant to consider the potential generalisability of our findings to real-world driving scenarios and different levels of vehicle automation. While our study was conducted in a controlled simulator environment focusing on SAE Level 3 automation, the insights gained regarding the impact of NDRT placement on drivers' attention management and gaze patterns may have implications for other levels of automation and real-world driving situations. As SAE Level 3 vehicles become more prevalent, the importance of understanding drivers' interactions with NDRTs will likely increase. Although the specific nature of NDRTs and the required level of driver engagement may differ across automation levels, the general principles of attention management and the potential for distraction remain relevant. Furthermore, it is relevant to note that the effects of NDRTs on drivers' gaze behaviour may depend on the specific type of NDRT. Our study focused solely on the use of video as the NDRT, suggesting that different types of tasks may influence the observed effects. Future studies are needed to investigate how different types of NDRTs beyond video watching, such as reading, typing, or engaging in conversation, may impact drivers' gaze behaviour and attention management strategies. Future research should investigate the extent to which our findings apply to different automation levels and explore how NDRT interactions may evolve as vehicle automation advances.

As a potential limitation, this study focused on understanding drivers' gaze patterns in a simulated driving environment using real-world recorded videos. The study lacked any evaluation of drivers' hazard detection capabilities or safety-critical take-over scenarios to measure drivers' readiness to take over. The assumed implications on safety are based on theoretical considerations grounded in previous studies that have assessed the effect of drivers' gaze behaviour on the forward roadway. Future studies are needed to systematically assess whether drivers can efficiently detect safety-critical elements in more realistic driving environments when engaged with NDRTs presented in HUDs to further validate these findings and their potential impact on road safety. This additional research may help to more comprehensively understand the relationship between NDRT engagement, gaze behaviour, and drivers' ability to respond to hazards in AVs.

Drivers were allowed to position their mobile NDRT in any desired location. Future studies could explore more accurate methods in classifying the "Unknown" areas, which could help reduce false positives when an NDRT is allowed. By better understanding where drivers are looking when their gaze falls outside the predefined AoIs, researchers and system designers can develop more precise attention monitoring systems and adapt NDRT permissions accordingly. Therefore, these findings may inform the future design of NDRT placement, ensuring that NDRTs are positioned within a DMS gaze detectable zone to enable continuous monitoring of drivers' visual attention status.

Lastly, it is important to acknowledge some limitations of our study and the Markov Chains approach. This approach assumes that gaze transitions do not rely on memory from other information other than the current state of the gaze location. In addition, it should be acknowledged that it may be reductionist for a precise picture of drivers' overall gaze behaviour. Also, the Markov Chains model does not take into account how salient elements in the dynamic road environment may influence drivers' gaze shifts, drawing conclusions only on the gaze transitions between static AoIs. Future work could address these limitations by developing more advanced models that incorporate memory effects and environmental factors.

Despite the limitations of this study, it provides evidence of the value of Markov Chains models for gaze fixation transitions as a tool for understanding drivers' attention management. As vehicle automation continues to advance, we need to develop a comprehensive understanding of how drivers' attention is affected by various interface designs and display characteristics (e.g., size, brightness, contrast, transparency) and establish guidelines for safe interactions with NDRTs.

In conclusion, this research opens up new avenues for investigation in the field of automotive user interfaces and makes significant contributions to the broader HCI. The insights gained from Markov Chain analysis—complementing traditional gaze concentration and dispersion metrics—may inform how new technologies change drivers' scanning strategies and provide a more comprehensive link to their hazard perception capabilities. The use of Markov Chains in studying NDRT engagement in AVs provides valuable lessons for HCI practitioners working on systems that require users to maintain situation awareness while engaging with technology.

Utimately, the goal is to design interfaces that support and minimise disruptions to drivers' attention management and maintain their situational awareness. The Markov Chains approach provides valuable insights to inform the design of in-vehicle interfaces for NDRTs that are better aligned with drivers' attention management strategies in AVs, contributing to the safe introduction of L3 automated driving. Furthermore, these findings may contribute to the design of adaptive and context-aware interfaces that promote safer and more effective interactions between users and complex technological environments, extending beyond automotive contexts to various domains.

This approach aligns with current trends in HCI research, particularly the growing interest in adaptive and context-aware interfaces. By providing a detailed understanding of how users allocate attention across different interface elements, our work lays the foundation for developing intelligent systems that can dynamically adjust based on user behaviour. This resonates with the HCI community's increasing focus on personalised and responsive user experiences in complex technological environments.

Our data-driven approach showcases how such methods may inform the development of more intuitive and responsive user interfaces in automotive contexts and across various domains of HCI. This study represents a significant step in bridging the gap between automotive interface design and general HCI principles, offering a methodology and insights that can be leveraged in diverse fields.

Furthermore, future research could build upon our findings by investigating the relationship between gaze behaviour during automated driving and subsequent driving performance after a TOR. While our study focused on attention allocation and gaze patterns during the automated driving phase, examining how these patterns correlate with drivers' ability to safely resume control could provide valuable insights. Such research could involve measuring reaction times, lane-keeping performance, and collision avoidance capabilities immediately following a TOR. This approach would help establish a more comprehensive understanding of how different NDRTs and their associated gaze behaviours impact overall driving safety in conditionally AVs.

Beyond automotive applications, our approach could inform HCI design in other attention-critical domains. For example, in aviation cockpits, industrial control rooms, and healthcare settings, the Markov Chain analysis could optimise information display layouts and support better attention management. Even in everyday technology, these insights could improve interface designs for multi-tasking across devices and applications. These potential applications demonstrate how our research contributes to the broader field of HCI, offering methodologies to enhance user interface design in complex, attention-demanding environments

By sharing these findings, we aim to support the broader HCI community's ongoing efforts to develop user-centred, safe, and efficient interfaces for increasingly complex technological systems.

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