Accident Analysis and Prevention 225 (2026) 108327

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

The impact of N-back-induced mental workload and time budget on takeover performance

Courtney M. Goodridge [a,*], Rafael C. Gonçalves [a], Ali Arabian [a], Anthony Horrobin [a], Albert Solernou [a], Yee Thung Lee [a], Audrey Bruneau [b], Yee Mun Lee [a], Natasha Merat [a]

[a] Institute for Transport Studies, University of Leeds, UK
[b] Toyota Motor Europe, Belgium

A R T I C L E I N F O

Keywords:
Mental
Workload
Automation
Takeover
Gaze
Time
Budget

A B S T R A C T

Mental Workload (MWL) refers to the specification of information processing capacity used for maintaining task performance. Some studies find no effects of high MWL on the timing and quality of takeovers, whilst others have found increases in crash risk and delayed response times. The effect of time budget – the time between event onset and an impending crash – is much clearer; drivers react faster when time budgets are smaller. However, no study has investigated whether the effects of a pure MWL interact with the effects of time budget during critical takeovers from a hands-off Level 2 (L2) driving system. A Bayesian multilevel modelling approach was used to quantify the direction, size, and uncertainty of the effects that MWL and time budget have on driver performance. Drivers (N = 37) used a hands-off L2 driving system: once while completing a pure MWL task (2-back) and another while monitoring the road. Rear-end conflicts were generated via lead vehicles decelerating with short (TTC = 3 s) or long (TTC = 5 s) time budgets. 2-back-induced MWL had no consistent or substantial impact on the timing or quality of takeovers. Conversely, drivers were faster to respond but more erratic in their post-takeover lateral control following events with smaller time budgets. We discuss the reasons for the absence of effects from the 2-back-induced MWL on takeover performance. One suggestion is that rear-end scenarios elicit automatised behaviours that do not rely upon cognitive control and thus remained unaffected by MWL. Conversely, scenarios that require cognitive control (e.g., lane change manoeuvres or hazard perception tasks) may be more susceptible to the detrimental effects of MWL during transitions of control.

1. Introduction

1.1. *Driver monitoring*

As the level of automation in road vehicles increases, the role of the human driver transitions from vehicle operator (SAE Level 0; SAE, 2021) towards system supervisor (SAE Level 2 and Level 3; SAE, 2021) or vehicle passenger (Level 4 and Level 5; SAE, 2021) (Biondi & Jajo, 2024). Crucially, for SAE Levels 2 (L2), 3 (L3), and 4 (L4), the human is still ultimately responsible for the safe resumption of control when the system has reached the limits of its Operational Driving Domain (ODD). How then, can we ensure that the driver is ready to re-engage with the dynamic driving task following periods of supervision? It is well established from aviation that humans are poor at monitoring systems (Parasuraman et al, 1993; 2003; 2018). Furthermore, research has consistently found that driver eye movements tend to be more dispersed and less focused on the road centre as the level of automation increases (Louw & Merat, 2017; Mole et al, 2019), alongside drivers focusing more on non-driving related tasks (NDRTs) (Carsten et al, 2012; Mueller et al, 2024).

Driver Monitoring Systems (DMS) aim to alleviate these safety issues; they refer to a selection of sensors and cameras that monitor whether the driver is alert, attentive, and ready to engage if a critical situation arises. If a driver's level of engagement falls below a particular level, a warning is provided; this might be to attend towards the road environment, or to place their hands on the steering wheel. The concept of a driver being "ready", "engaged", and/or "available" is known as Driver Readiness (DR). DR (also known as driver availability; Marberger et al (2017)) can be defined as the probability of a successful intervention during a takeover situation (Georg et al, 2017). An assumption of DR is that during automation, a driver is removed from the perceptual-motor control loops that are vital for efficient and safe driving (Merat et al,

* Corresponding author.
E-mail address: c.m.goodridge@leeds.ac.uk (C.M. Goodridge).

https://doi.org/10.1016/j.aap.2025.108327
Received 14 April 2025; Received in revised form 27 October 2025; Accepted 17 November 2025
Available online 25 November 2025

2019; Mole et al, 2019). Therefore, drivers might not be capable of resuming control of the dynamic driving task safely after a takeover request (TOR) has been delivered. As such, there has been increased interest in understanding DR; namely, how to estimate it, and what factors impact it during critical situations.

One of the challenges of DR is that it is an abstract concept that cannot be directly measured. Therefore, it has generally been operationalised via constructs that are associated with a driver's ability to take over from automation (Gonçalves et al, 2024; Hecht et al, 2019). Readiness has often been split into two main categories; motoric and cognitive readiness (Gonçalves et al, 2024; Mioch et al, 2017; Kim et al, 2022). Motoric readiness refers to the driver being physically available to regain control of the vehicular controls. This can manifest through body pose (e.g., the head being in a position such that visual stimuli can be perceived and reacted to) alongside hand and feet positioning (e.g., positioning hands and feet such that they can control the vehicle) (Mioch et al, 2017). This is particularly pertinent for hands-off L2 driving, where drivers may not be required to have their hands on the steering wheel. Cognitive readiness refers to the driver having sufficient cognitive resources available to them in order to attend to, and process, relevant information during takeover situations. It is therefore proposed that sufficient DR will result in smoother transitions of control back towards the main driving task.

The driving task has often been described as a collection of driving *subtasks* (performed sequentially or simultaneously) (Engström, 2011; Engström et al., 2017b). Some of these subtasks are said to be automatised and governed by strong neural pathways. Conversely, some subtasks may require cognitive control as they have not been extensively practised or are tasks associated with inherently uncertain situations (Engström et al., 2017b). The Cognitive Control Hypothesis (CCH) encapsulates how these differing perspectives interact to inform how the loading of cognitive resources may impact manual driving performance. CCH proposes that elevated MWL selectively impairs driving subtasks that require cognitive control whilst leaving automatised subtasks unaffected. Support for the CCH has been found in a range of manual driving studies (see Engström et al., 2017a,b for a review); however, it is unclear how (or even if) the CCH translates to subtasks implicated in transitions of control from intermediate and higher levels of automation.

1.2. Takeover performance

Takeover safety is largely governed by two aspects: the time between event onset and the impending collision (known as the "time budget"), and the effectiveness of driver action (McDonald et al, 2019). If a driver is motorically and cognitively ready, can decide on an action, and can effectively execute that action within a time budget, the driver is likely to avoid a collision. Whilst collisions are a useful measure of takeover performance from a safety perspective, they provide an "all or nothing" description of takeover quality. In reality, there are instances where a takeover is suboptimal but there has not been a resultant collision. A range of metrics aim to measure takeover quality including lane position statistics (i.e., the standard deviation of lane position, SD_{LP}) and the average derivatives of driver control inputs (i.e., lateral acceleration/jerk or longitudinal deceleration/negative jerk). Extremities in these measures may not result in a crash but may impact other vehicles to the side or behind the ego-vehicle, resulting in poor-quality takeovers.

The takeover process after an automated system ceases to operate involves the driver regaining motor and cognitive readiness in order to reengage with a number of operational factors including the reduction of longitudinal speed, re-grasping the steering wheel, and consequently stabilising the vehicle (Marberger et al, 2018). A takeover process model proposed by Zeeb et al (2015) focused on the underlying processes of driver takeover whilst completing a secondary task. The model comprised four main elements; orienting gaze towards the road, motor readiness, cognitive processing (which includes perceiving elements within the visual scene), and the takeover reaction itself. This model assumed that motor readiness and cognitive processing could be completed in parallel and thus detriments of cognitive readiness did not necessarily impact motor coordination. Zeeb et al (2016) supported this prediction, finding no effect of visual-cognitive non-driving related task (NDRT) type (e.g., engaging in email, news, or a video task, as well as a no task baseline) when measuring hands-on reaction time.

Whilst there have been a lot of research on takeover performance regarding "highly automated" or Level 3 systems (Gold et al, 2013; 2015; 2016, Melnicuk et al, 2021; Pan et al, 2023; Pan et al, 2025; Radlmayr et al, 2014; Wu et al., 2019a; 2019b), far fewer have investigated the impact of pure MWL on takeover performance from "partially automated" L2 systems. MWL is one construct of DR that has received high interest; typically, it refers to the quantity of mental resources that are demanded and/or are used in order to maintain task performance (De Waard, 1996). Whilst the driver's eyes might still be on the road during a highly loading secondary task, the cognitive resources available to the driver for transitions of control might be low. As such, their cognitive readiness may be low, and thus their takeover performance impaired. Despite this implicit expectation, empirical results on the influence of MWL on takeover performance is mixed.

Louw et al (2017) found that MWL did not affect crash risk or the percentage of road gaze fixations within 3 s of a takeover request (TOR) when taking over from a hands-off L2 driving system. Louw et al (2017) suggested that higher load could be indicative of less anticipatory responses (i.e., responding *after* the onset of lead vehicle brake lights) and more crashes, however inferential analysis did not support this claim. Conversely, Choi et al (2020) found that drivers who produced faster transitions of control reported higher workload. Choi et al (2020) proposed that this was indicative of high MWL making drivers more aware of potential danger during automated driving, thus causing drivers to place their hands on the steering wheel faster. However, this implies that higher MWL produces more anticipatory responses; the opposite of Louw et al's (2017) proposal. Recent work by Sun & He (2025) support Louw et al's (2017) suggestion; they found that increased MWL impaired driving anticipation resulting in later preparations for hazards during L2 driving. Despite these findings, other studies have found no negative impacts of high MWL. Wu et al (2019) found no effect of MWL on steering initiation time or steering wheel variability one second after a lane change during a vehicle avoidance task. Choi et al (2020) also found that N-back difficulty had no consistent or substantial effects on response time, steering variance between the initiation of the steering to the lane crossing, or steering angle variance after lane crossing for a vehicle avoidance task. However, one negative effect of MWL was the association with an increase in time margin between the initiation of steering and consequential lane crossing; a 300 ms increase for every increment of MWL. This indicates that drivers were less ready to initiate their manoeuvre to avoid an obstacle during high MWL conditions. Given that lane changes have been associated with elements of cognitive control (i.e., decision making, see Goncalves et al., 2022), this latter result from Choi et al (2020) could provide initial evidence that the CCH may apply to transitions of control.

It is not clear why there is such inconsistency in the effects of MWL on takeover quality from L2 driving. For example, many studies have the same manipulation of MWL (i.e., N-back) and utilise similar critical events (i.e., lead vehicle deceleration and/or obstacle avoidance) (Choi et al, 2020: Louw et al, 2017; Sun & He, 2025; Wu et al, 2019). One suggestion is that the true population-level effect of MWL on takeover quality – if it is indeed detrimental – is very small. If this is the case, more precise analytic methods will be necessary to estimate it, alongside continuing replications. Rather than focusing on comparing point mean estimates between experimental conditions, as has been done in prior studies (Choi et al, 2020: Louw et al, 2017; Sun & He, 2025; Wu et al, 2019), more emphasis should be placed on estimating the size and variance of the effects of MWL (see Cummings, 2014).

Whilst the effect of MWL on takeover performance is largely inconsistent, the criticality of the scenario (operationalised via time budget) reliably impacts takeover performance. A typical finding in the literature is that scenarios with smaller time budgets (i.e., scenarios with higher criticalities) tend to result in faster reactions, but poorer quality takeovers (Gold et al, 2013). A *meta*-analysis on studies investigating time budgets for L3 systems found that response times increased by .33 s for every 1 s increase in time budget (Gold et al, 2018). For SAE levels 2–4, McDonald et al (2019) found similar findings; a .27 s increase in takeover time for every 1 s increase in time budget. Manipulating the time budget of an event has also been found to reduce the quality of post-takeover vehicle control. Smaller time budgets have been associated with larger maximum longitudinal decelerations and lateral accelerations (Wan & Wu, 2018), increased likelihood of crashing (Wan & Wu, 2018), and larger standard deviations of lateral position and steering wheel angle (Mok et al., 2015a; 2015b). Whilst it is clear that time budget influences takeover performance, few studies have investigated whether MWL interacts with this effect. Wan & Wu (2018) found that some of the negative effects of time budget on takeover performance (minimum time to collision) were exacerbated when drivers engaged in secondary tasks. However, these secondary tasks involved taking drivers visual attention away from the forward roadway (e.g., reading, typing, watching videos). A study by Du et al (2020) found no effect of time budget, MWL, or any interaction for takeover times, only larger maximum accelerations for events with smaller time budgets. However, the N-back task used in this study had substantial visual and manual elements to the distraction. In the context of L2 systems, it is crucial to understand whether a purely cognitive NDRT interacts with the time budget of a potentially critical scenario. In the real world, it is likely that there will be situations where drivers of L2 systems will be monitoring the road environment with their eyes on the road, a warning is delivered because the vehicle has reached the limits of its Operational Driving Domain (ODD), and yet the driver's cognitive readiness is depleted due to engaging in NDRTs (such as hands-free phone conversations). The exacerbation, or lack thereof, of negative driver performance due to increased MWL must be investigated within the laboratory to fully understand the consequences.

1.3. Gaze behaviour

Alongside takeover performance, it is also important to understand how eye movements change during transitions of control. Visual attention is commonly associated with a driver's level of cognitive readiness (Gonçalves et al, 2024) and is vital when resuming control of the vehicle. During critical takeovers, drivers transition from a supervisory role to active control of the vehicle (Deniel & Navarro, 2023). Without sufficient visual exploration, this could lead to poor decision making, poor steering performance, and ultimately worse quality takeovers. Driver gaze tends to be more constrained under high MWL during automated driving; this can manifest as a reduction in the complexity of gaze transitions (Goodridge et al, 2024) or via a reduction in the dispersion of horizontal gaze (Gold et al, 2016; Louw & Merat, 2017; Wilkie et al, 2019). The latter of these effects has been comprehensively observed in loaded drivers during manual driving (Reimer, 2009; 2010; 2012; Sodhi et al, 2002). It has not yet been established whether the reduction of horizontal gaze dispersion under high MWL is of a similar size during partially automated driving as it is for manual driving. Wilkie et al (2019) did investigate horizontal gaze dispersion with and without MWL, and in manual and automated driving conditions. Although they did not report an analysis of the interaction effect between these variables, data visualisations imply that an interaction might be present.

Research has also investigated changes in gaze behaviours following takeovers. Whilst vehicle dynamics data is a key indication of takeover performance, gaze behaviours provide a continuous and temporal indication of driver state during the takeover (Du et al., 2020a; 2020b). Such information may prove useful for predicting future manual driving performance following a takeover. Once again, the criticality of the situation may influence driver state, with reduced time budgets implying higher urgency and thus potentially more cognitive resources for adequate takeover performance. A review of the effects of takeover criticality on gaze behaviours notes that the manipulation of criticality largely combines the consequences of failure (head on collisions, deviating from a lane) with time budgets (Deniel & Navarro, 2023). However, a general finding is that higher criticalities result in drivers being quicker to reorientate their gaze back towards the road centre (Hyde, 2018; Louw et al, 2015). Despite this being an optimal reaction, it has been suggested that the exploration of the scene by the driver is more dispersed and less focused on the road (Hyde, 2018).

Du et al (2020) investigated whether severe (TTC = 4 s) or less severe (TTC = 7 s) events produced changes in eye movements during takeover transitions. The standard deviation of horizontal gaze was not affected; however, the rate of blinking was found to increase for takeovers with smaller time budgets. The peak of the difference in blinking rate occurred 5 s post-TOR. Du et al (2020) claimed that blink inhibition indicated that drivers paid greater attention to critical scenarios with smaller time budgets in order to support decision making. Support from this comes from work suggesting that blinking decreases when more information is required for processing (Veltman & Gaillard, 1996). However, there are a number of limitations to this study. Firstly, the statistical model used to analyse these data was mis-specified. The degrees of freedom used in the Analysis of Variance implied that the sample size was over 500 whereas the true sample was only 102. Furthermore, the difference in the number of blinks between 4 s and 7 s time budgets was approximately one blink over a 30 s period. Small effect sizes and inflated degrees of freedom are indicative of pseudo-replication of the sample (Lazic, 2010), whereby the repeated measures design is not specified correctly within the analytic model structure. Whilst Du et al (2020) claim that blink inhibition is indicative of higher arousal for more critical conditions, the biased p values associated with the statistical tests mean these results should be interpreted with caution.

1.4. Current work

Whilst previous research has investigated the impact of MWL (Choi et al, 2020; Zhang et al, 2019) and time budget (Mok et al., 2015a) on takeover performance, these have largely been investigated independently without understanding their interaction. Studies that have investigated their interaction have usually focused on NDRT variants that have cognitive, visual, and manual elements (Mok et al., 2015b; Wan & Wu, 2018). Purely cognitive tasks, such as auditory N-back or serial addition tasks (Du et al, 2020) have been focused on less. By "purely cognitive", we refer to a task that does not require the driver to divert their eyes or body away from safety critical driving activities and locations. This study aimed to investigate how drivers responded if they are required to take back control from a hands-off L2 vehicle. More specifically, what is the impact of increasing MWL on the timing and quality of takeovers, the influence on eye movements during automation and during post-takeover manual driving, and whether these effects are exacerbated by the time budget of a potential rear-end collision.

2. Materials and methods

2.1. Participants

41 participants were recruited via the University of Leeds driving simulator participant pool. However, three participants were removed before data analysis, as they did not follow the experimental instructions, or because eye tracking data was not captured correctly. After removing invalid responses (collisions, drivers who had their hands on the wheel during the TOR, physiologically implausible reaction times), a further participant was removed from the dataset. The remaining 37 participants (15 females, 22 males, mean age = 39.05, range = 22–65) all had normal or corrected to normal vision. All

participants had a valid UK driving license (mean number of years = 18, range = 4–43) and were regular drivers (mean annual miles = 9067.56, range 5000–20,000).

2.2. Apparatus and materials

The experiment was conducted at the University of Leeds Driving Simulator (see Fig. 1). The motion-based driving simulator consisted of a Jaguar S-type cab encased within a 4 m spherical projection dome. The dome has a 300° field of view projection to render the driving environment. Driver controls were fully operational, with pedals and steering providing haptic feedback. This provided participants with conditions that replicated real-world driving. Longitudinal and lateral movement was provided via a hexapod motion base and a 5 m × 5 m X-Y table. Gaze data were collected using a Seeing Machines Driver Monitoring System eye tracker sampling at 60 Hz. The NASA Task Load Index (NASA-TLX) was used to measure subjective mental workload (Hart & Staveland, 1988) and consisted of 6 subscales; mental, physical, and temporal demands, as well as frustration, effort and performance.

2.3. Design

This experiment had a 2 x 2 repeated measures design; the two within-participants factors were MWL and the criticality of the takeover event. MWL was manipulated over two levels: a no-load condition (monitoring the road environment during hands-off L2 driving) and a high load condition (completing a verbal response delayed recall task; 2-back – see Mehler et al., 2011), during hands-off L2 driving. 2-back has been used as a task to increase MWL during manual (Reimer, 2009; Reimer et al, 2010; Wang et al, 2014) and automated driving (Goodridge et al, 2024; Choi et al, 2020; Radlmayr et al, 2019; Wilkie et al, 2019).

Event criticality was operationalised by changing the time budget of a potential rear-end conflict. This was manipulated over two levels: a larger time budget for less severe events (time to collision (TTC) = 5 s) allowed drivers to successfully takeover in most critical events, whereas a smaller time budget (TTC = 3 s) produced a severe event that could lead to a rear-end collision if the driver was not paying sufficient attention. These specific values were chosen as previous research has demonstrated that a 3 s TTC produces highly critical situations, whereas 5 s TTCs allow drivers sufficient time to takeover (Gold et al, 2013; Mok et al, 2015; Louw & Merat, 2017). The experiment was comprised of two drives on a 3-lane UK motorway. During one drive, participants completed 2-back during the automated period; the other drive involved no secondary task. Each drive lasted approximately 35 minutes and was comprised of 10 discrete events. Each event consisted of 30 s of manual driving followed by approximately two minutes of automated driving. After two minutes of automated driving, a takeover request (TOR) was delivered by short auditory tone and the shifting of a steering wheel Human-Machine Interface (HMI) icon from green (automation engaged) to flashing red (takeover required) (see Fig. 3). Four of these events were critical; two had a TTC of 3 s (deceleration rate of 5.55 m/s^2), two had a TTC 5 s (deceleration rate of 2 m/s^2). The deceleration of the lead vehicle occurred as soon as the TOR was triggered. The remaining six events were non-critical; two without a lead vehicle and four with a lead vehicle that did not decelerate once the TOR was activated. These were included to guard against learning effects such that the presence of a lead vehicle was not always associated with a critical event. Analysis of the event order revealed no effects for any of the metrics (see supplemental analysis: https://github.com/courtneygoodridge/takeover_performance_cogload_time_budget). Lead vehicles appeared from the left-hand lane before the automated system was engaged and maintained a distance of 25 m (see Fig. 2). Ambient traffic in the left and right lanes flowed consistently to provide sufficient bottom-up sensory input to facilitate driver scanning. All TORs were delivered on straight sections of motorway to avoid confounding effects of road curvature influencing takeover performance.

Fig. 1. University of Leeds Driving Simulator.

2.4. Procedure

Informed consent was obtained, and standardised procedural instructions were delivered before participants began the study. All procedures were approved by the University of Leeds Research Ethics Committee (Reference code: 2022–0353-206).

Participants completed pre-drive questionnaires (the data for which is not reported within this manuscript). A practice session allowed participants to become familiar with the vehicle dynamics and task requirements. During this session, participants were walked through the Human-Machine Interface (HMI) that indicated the state of the automation (see Fig. 3), completed a static N-back, were shown how the automated system engaged, and how they could disengage the automated system. Participants were instructed to remove their hands and feet away from the steering wheel and pedals once the automated system was engaged. During the practice trial, a non-critical takeover with a lead vehicle in front was used; N-back was not completed during the practice drive.

Participants started the drive on a motorway slip road and were instructed to position the vehicle in the centre of the middle lane, maintaining a speed of 70 MPH. After 30 s of manual driving, the automated system engaged; participants removed their hands from the steering wheel and their feet away from the pedals. The activation of the automated system was indicated via an auditory tone and the HMI changing from greyed out to green (see Fig. 3). After two minutes of hands-off L2 driving, a TOR was issued which was characterised by the HMI icon flashing red and an auditory tone. Participants could take over via 3 different modes: turning the steering wheel in either direction by more than 2°, pressing any of the operational pedals, or pressing a micro-switch button strapped to the steering wheel. During piloting, it became obvious that some drivers wanted a way of deactivating the automated system without touching the operational controls; this was particularly true during non-critical trials. Hence the inclusion of the micro-switch button allowed drivers this option. Participants had 10 s to disengage the automation, after which the automated system automatically disengaged back into manual driving mode. Overall, a majority of drivers (84 %) used the operational pedals to deactivate the automated system during critical trials due to the criticality of the event; the remaining 16 % used the microswitch or initiated steering to change lanes. After the takeover, participants drove manually for approximately 30 s before the automated system reengaged to begin the next trial. Participants were explicitly instructed during the practice to rejoin the middle lane if they left it during their takeover. Automation would not engage until they returned to the middle lane. Overall, there were 10 discrete events per drive and each drive lasted approximately 35

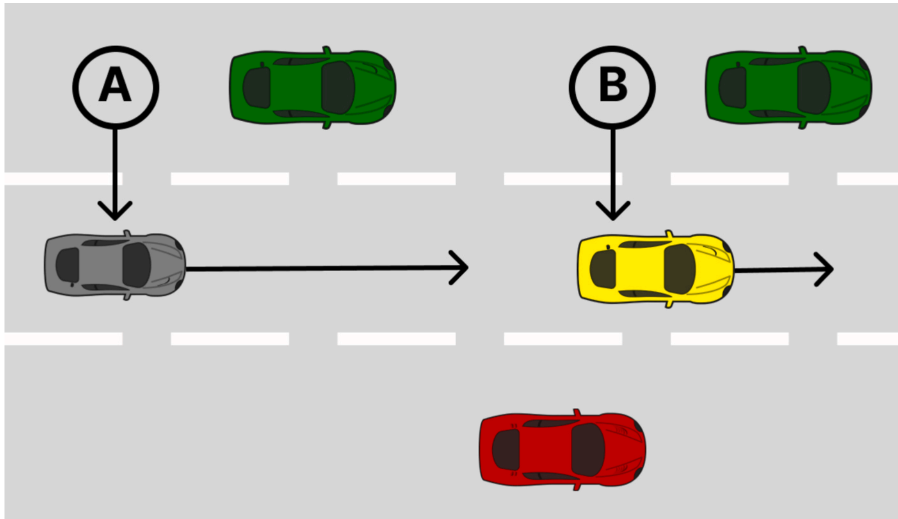

Fig. 2. Schematic representation of an event and adapted from Goodridge et al (2024). Ego vehicle (A) and lead vehicle (B) travelling on a 3-lane motorway. Lead vehicles entered from the left lane and matched the ego vehicle's speed at a distance of 25 m. After 2 minutes of automated driving, the lead vehicle decelerated at 5.55 m/s^2 (TTC = 3 s) or 2 m/s^2 (TTC = 5 s) for critical trials. For non-critical trials, a TOR was delivered but the lead vehicle did not decelerate.

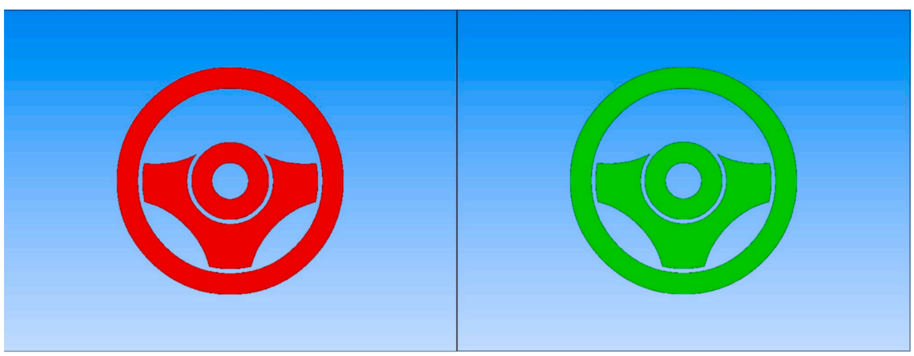

Fig. 3. These icons were used to indicate system status. A green steering wheel indicated the that the L2 driving system was activated. When a TOR was issued, the red steering wheel flashed, indicating that the driver needed to take over. This flashing continued until the vehicle was back into manual driving mode. During manual driving, the steering wheel was greyed out. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

minutes. After each drive participants filled out a NASA-TLX to measure subjective ratings across each of the 6 subscales. Analysis of the mental demand subscale was conducted in a previous manuscript, finding that subjective scores doubled on average from 38.994 during no N-back drives to 78.705 during N-back drives (see Goodridge et al, 2024 for full analysis). At the end of the experiment, post-drive questionnaires we also filled out (the data for which are not reported within this manuscript).

2.5. Statistical modelling

2.5.1. Analytic approach

A Bayesian modelling approach was used to analyse the data within this manuscript. The posterior distributions were estimated using the No-U-Turn sampler in the brms package in R (Bürkner, 2017). For model parameters that predicted the expected value of the dependent variable, weakly informative regularising priors were used. Maximal random effects structures were specified within each of the models to account for between-participant variability. Model fits were assessed via graphical assessment of the posterior predictive checks. The summary of this can be found in the supplemental material (https://osf.io/e4rkj/overview). Data and analysis code can be found in the following link (https://github.com/courtneygoodridge/takeover_performance_cogload_time_budget).

Many of the response variables analysed in the following sections follow non-Gaussian distributions. This makes interpreting the parameter values directly difficult because the expected value of the outcome variable is not one of the distribution's parameters (as is the case for a Gaussian model distribution; the expected value is the mean, μ). Therefore, the Marginal Effects at the Representative values (MER) were computed which referred to the expected value of a takeover metric at a given level of the covariate (Heiss, 2022; Nguyen, 2023; Perraillon, 2019).

3. Results

3.1. Response times

3.1.1. Model fitting

Response times have unique distributional characteristics; they are typically positively skewed and non-negative (Wagenmakers et al, 2007). Another property of response times is that there are physiological limits to how fast they can be because human response times are not instantaneous. A Shifted Log-Normal distribution was used to model response times. The shift parameter (δ) determines the location of the distribution along the X axis, effectively shifting it to the right by certain amounts. This parameter acts as a minimum boundary, such that all values in the distribution are greater than the shift value. In the case of response times, the δ parameter can account for non-decision time given that reactions do not occur instantaneously. The inclusion of this parameter produced improved inferences on expected response times alongside adding some mechanistic application of real human responses (Lindeløv, 2019). Two response time variables were measured in this analysis. Brake reaction time (RT_B) referred to the time from the TOR until the driver applied 1 Newton-metre (nm) of brake force to the brake pedal. Hands-on steering wheel time (RT_{HO}) referred to the time from the TOR until the driver placed their hands on the steering wheel. The population mean, μ, of these response time metrics was modelled via a linear combination of an intercept (β_0), N-back (N, β_N), time budget (C, β_T), and an interaction term between these variables (NT, β_{NT}). The N-back task was parameterised as $N \in \{0, 1\}$ where $N = 1$ corresponds to the presence of the N-back during hands-off L2 driving. Time budget was parameterised as $T \in \{0, 1\}$ where $T = 1$ corresponds to the influence of a TTC = 5 s event relative to the TTC = 3 s event. These parameterisations indicate the absence or presence of a categorical effect that may be expected to shift the outcome. In the current analysis, the parameters β_N and β_T represent the average effect of N-back and the contrast between TTC = 3 s and TTC = 5 s, respectively.

The model structure is defined as follows:

$$Y_{ij}\ ShiftedLogNormal\left(\mu_{ij}, \sigma_e, \delta\right)$$

$$\mu_{ij} = \left(\beta_0 + \beta_{0_j}\right) + \left(\beta_N N_i + \beta_{N_j} N_i\right) + \left(\beta_T T_i + \beta_{T_j} T_i\right) + \left(\beta_{NT} NT_i + \beta_{NT_j} NT_i\right)$$

$$\begin{bmatrix} \beta_{0_j} \\ \beta_{N_j} \\ \beta_{T_j} \\ \beta_{NT_j} \end{bmatrix} MVN\left(\begin{bmatrix} \beta_{0_j} \\ \beta_{N_j} \\ \beta_{T_j} \\ \beta_{NT_j} \end{bmatrix}, S_\beta\right)$$

$$S_\beta = \begin{pmatrix} \sigma^2_{\beta_{0_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{N_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{T_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{0_j}} & \sigma^2_{\beta_{N_j}} & \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{T_j}} & \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{0_j}} & \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{N_j}} & \sigma^2_{\beta_{T_j}} & \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{0_j}} & \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{N_j}} & \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{T_j}} & \sigma^2_{\beta_{NT_j}} \end{pmatrix} \tag{1}$$

This model set up assumed that Y was Log-Normally distributed with a mean (μ), a standard deviation (σ), and a shift parameter (δ). The shift parameter moved the entire distribution towards the left or right of the x axis and when δ = 0, the distribution was a Log-Normal distribution with two parameters: μ and σ. Y denoted the response time metric, i specified the condition of each variable, j specified the participant, and S_β corresponded to the variance and covariance parameters.

3.1.2. Brake reaction time (RT_B)

The coefficient posterior means and 95 % CIs alongside the probability of direction are shown in Table 1. The model predicted no substantial or reliable effect of MWL on brake reaction times. However, the posterior predictions indicated that drivers were slower to initiate braking when TTCs were high (TTC = 5 s; RT_B = 1.283 s) versus when TTCs were low (TTC = 3 s; RT_B = 1.156 s) (see Fig. 4C). The average increase in RT_B when TTCs were higher was 0.127 s ($MER_{RT_B} = 0.127$, [CI: 0.016, 0.235]), however the credible intervals implied that reaction times could have increased by as much as 0.235 s, or as little as 0.016 s (effectively 0).

Table 1
Posterior means and 95% CIs for parameters predicting RT_B.

Fixed effects	Dependent variable:	
	RT_B	*pd*
β_0	−0.429 (−0.659, −0.176)	99.90 %
β_N	−0.018 (−0.167, 0.132)	60.02 %
β_T	0.167 (0.026, 0.321)	99.08 %
β_{NT}	−0.063 (−0.262, 0.125)	73.98 %
Participants	37	
Observations	241	

3.1.3. Hands-on steering wheel reaction time (RT_{HO})

A similar effect was observed for hands-on steering wheel reaction time. There was no substantial or consistent effect of MWL, however participants were slower to place their hands on the steering wheel when faced with higher TTCs (TTC = 5 s; RT_{HO} = 1.427 s) versus lower TTCs (TTCs = 3 s; RT_{HO} = 1.286 s). There was slightly more uncertainty regarding the direction and magnitude of the effect that time budget had on hand-on steering wheel reaction time. This was reflected in the *pd*, which indicated a 97 % probability that the effect was positive (see Table 2), and in the 95 % CIs ($MER_{RT_{HO}} = 0.140$, [CI: −0.016, 0.299]) which highlighted that some of the most probable parameter values for the effect of time budget could be near 0 (see Fig. 5C).

3.2. Post-takeover manual driving

3.2.1. Model fitting

Lane position variability (SD_{LP}), mean lateral accelerations (M_{LA}), and mean decelerations (M_D) were used to assess post-takeover manual driving performance. SD_{LP} was computed by taking the standard deviation of lane position during 30 s of manual driving once the vehicle was in manual driving mode. Mean lateral accelerations and mean decelerations were calculated during the same 30 s period. This is in line with previous research that has focused on driving performance during the first 60 s post-automation (Melnicuk et al, 2021; Merat et al, 2014; Samani et al, 2022).

Mean deceleration had unique distributional properties whereby the distribution was negatively skewed and was comprised of negative values. To account for this, mean deceleration was modelled using a skew normal distribution. Skew normal distributions include an extra parameter, α, that generalizes the normal distribution to allow for non-zero skewness. The α determines the degree and direction of skewness. A positive α indicates a positive (right) skew, whilst a negative α indicates a negative (left) skew. The paramertisation of the parameters for the intercept (β_0), N-back (when $N \in \{0, 1\}$, β_N), time budget (when $T \in \{0, 1\}$, β_T), and the interaction term (NT, β_{NT}) were the same as the response time models:

$$Y_{ij}\ SkewNormal\left(\mu_{ij}, \sigma_e, \alpha\right)$$

$$\mu_{ij} = \left(\beta_0 + \beta_{0_j}\right) + \left(\beta_N N_i + \beta_{N_j} N_i\right) + \left(\beta_T T_i + \beta_{T_j} T_i\right) + \left(\beta_{NT} NT_i + \beta_{NT_j} NT_i\right)$$

$$\begin{bmatrix} \beta_{0_j} \\ \beta_{N_j} \\ \beta_{T_j} \\ \beta_{NT_j} \end{bmatrix} MVN\left(\begin{bmatrix} \beta_{0_j} \\ \beta_{N_j} \\ \beta_{T_j} \\ \beta_{NT_j} \end{bmatrix}, S_\beta\right)$$

$$S_\beta = \begin{pmatrix} \sigma^2_{\beta_{0_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{N_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{T_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{0_j}} & \sigma^2_{\beta_{N_j}} & \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{T_j}} & \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{0_j}} & \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{N_j}} & \sigma^2_{\beta_{T_j}} & \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{0_j}} & \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{N_j}} & \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{T_j}} & \sigma^2_{\beta_{NT_j}} \end{pmatrix} \tag{2}$$

Lateral post-takeover manual driving metrics were positively skewed and thus were modelled via a Log-Normal distribution. The shift parameter was removed as it was possible to have values of lane position

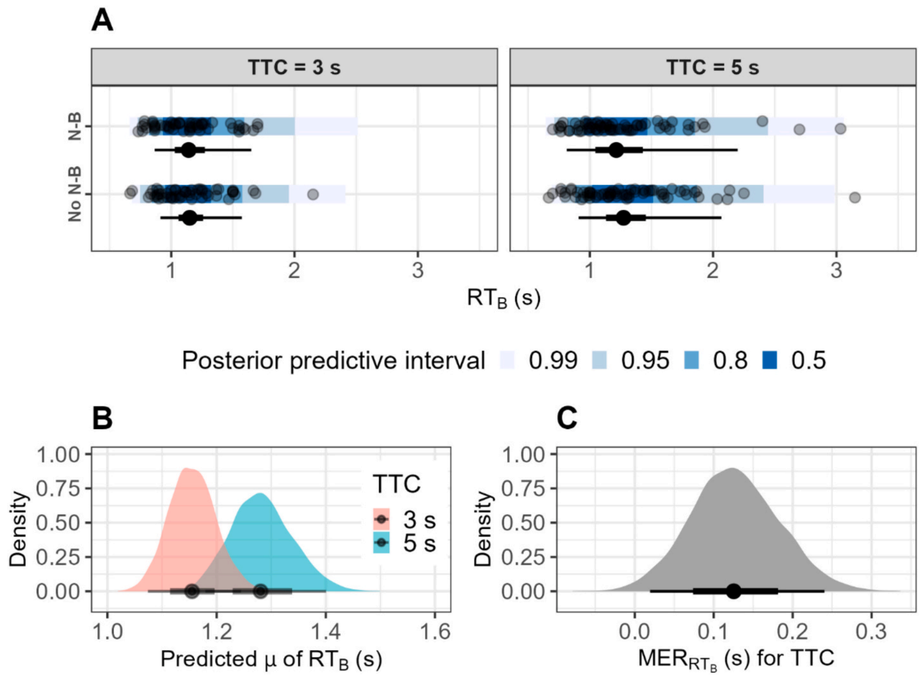

Fig. 4. A) Posterior predictive bands and posterior distribution of means plotted against raw data for RT_B. The point-interval plot highlights the predicted mean differences between N-back (N-B)/no N-back (No N-B) and time budget (TTC = 3 s/TTC = 5 s) alongside 50 % and 95 % credible interval bars. B) Posterior predictions of the expected RT_B for each time budget. C) Marginal Effect at the Representative value (MER) of time budget on RT_B (MER_{RT_B}).

Table 2
Posterior means and 95% CIs for parameters predicting RT_{HO}.

Fixed effects		
	Dependent variable:	
	RT_{HO}	*pd*
β_0	−0.269 (−0.484, −0.065)	99.70 %
β_N	−0.038 (−230, 0.146)	65.73 %
β_T	0.156 (−0.012, 0.328)	96.63 %
β_{NT}	−0.073 (−0.308, 0.146)	73.38 %
Participants	37	
Observations	241	

variability and lateral accelerations that were close to 0. The parametrisation of the parameters for the intercept (β_0), N-back (when $N \in \{0,1\}$, β_N), time budget (when $T \in \{0,1\}$, β_T), and the interaction term (NT, β_{NT}) were the same as the response time models:

$$Y_{ij}\ LogNormal\left(\mu_{ij}, \sigma_e\right)$$

$$\mu_{ij} = \left(\beta_0 + \beta_{0_j}\right) + \left(\beta_N N_i + \beta_{N_j} N_i\right) + \left(\beta_T T_i + \beta_{T_j} T_i\right) + \left(\beta_{NT} NT_i + \beta_{NT_j} NT_i\right)$$

$$\begin{bmatrix} \beta_{0_j} \\ \beta_{N_j} \\ \beta_{T_j} \\ \beta_{NT_j} \end{bmatrix} MVN\left(\begin{bmatrix} \beta_{0_j} \\ \beta_{N_j} \\ \beta_{T_j} \\ \beta_{NT_j} \end{bmatrix}, S_\beta\right)$$

$$S_\beta = \begin{pmatrix} \sigma^2_{\beta_{0_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{N_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{T_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{0_j}} & \sigma^2_{\beta_{N_j}} & \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{T_j}} & \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{0_j}} & \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{N_j}} & \sigma^2_{\beta_{T_j}} & \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{0_j}} & \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{N_j}} & \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{T_j}} & \sigma^2_{\beta_{NT_j}} \end{pmatrix} \quad (3)$$

Model set ups in equations (2) and (3) proposed that Y was Skew-Normally distributed and Log-Normally distributed, respectively. Y denoted the post-takeover manual driving metric, i specified the condition of each variable, j specified the participant, and S_β corresponded to the variance and covariance parameters.

3.2.2. *Mean deceleration* (M_D)

Posterior predictions highlighted that time budget had a substantial effect on braking behaviour following a TOR (see Table 3). Mean deceleration rates were predicted to be smaller when time budgets were larger (TTC = 5 s; M_D = -1.704 m/s^2) versus when time budgets were smaller (TTC = 3 s; −3.222 m/s^2) (MER_{M_D} = 1.518, [CI: 1.137, 1.880]) (see Fig. 6). This suggested that drivers initiated harsher decelerations when time budgets were smaller. Model estimates predicted no consistent or substantial effects of MWL on mean decelerations.

3.2.3. *Mean lateral acceleration* (M_{LA})

The posterior predictions highlighted a fully crossed interaction between MWL and time budget for the effect of mean lateral acceleration. For the critical events with small time budgets (TTC = 3 s), mean lateral accelerations were higher during no task conditions (M_{LA} = 0.259 m/s^2) versus then drivers were under high MWL (M_{LA} = 0.209 m/s^2). Conversely, when time budgets were large (TTC = 5 s) mean lateral accelerations were larger when drivers were under high MWL (M_{LA} = 0.259 m/s^2) versus when they were not (M_{LA} = 0.211 m/s^2) (see Fig. 7). Whilst this effect was small (an approximate 0.1 m/s^2 flip across the conditions) it was consistent, with high confidence regarding the probability of direction (see Table 4). This effect implied that for small time budgets, steering manoeuvres were less aggressive when drivers had high MWL. Conversely, when time budgets were higher, drivers under high MWL produced more aggressive steering manoeuvres.

3.2.4. *Standard deviation of lane position* (SD_{LP})

The coefficient posterior means and 95 % CIs alongside the probability of direction are shown in Table 5. The model estimates predicted that the SD_{LP} was lower when TTCs were higher (TTC = 5 s; SD_{LP} = .251 m) versus when TTCs were lower (TTC = 3 s; SD_{LP} = .360 m) ($MER_{SD_{LP}}$ = −0.108, [CI: −0.203, −0.020]) (see Fig. 8C). This suggested that lateral

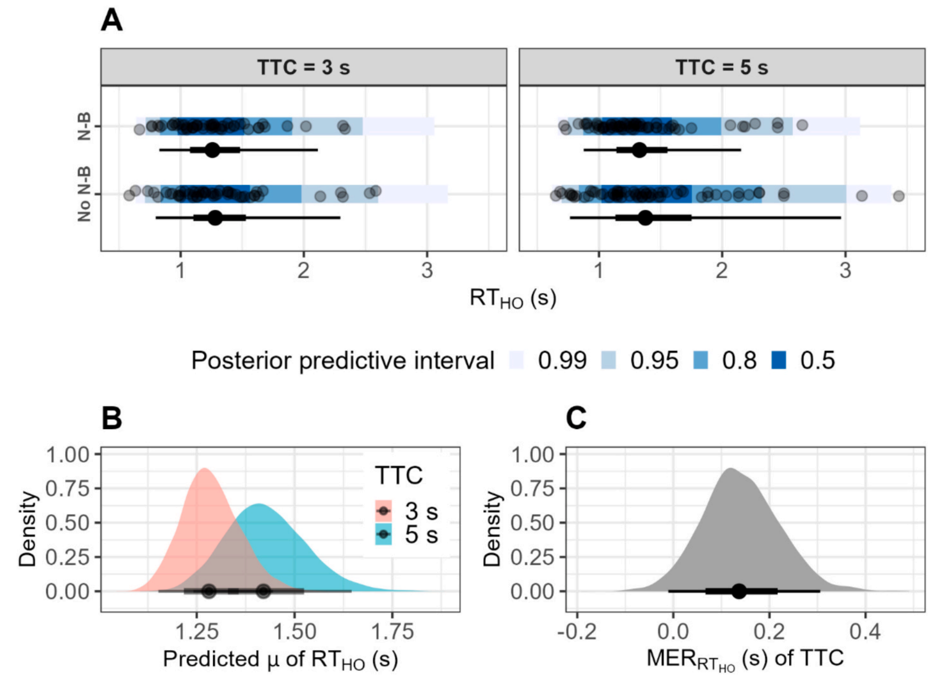

Fig. 5. A) Posterior predictive bands and posterior distribution of means plotted against raw data for RT_{HO}. The point-interval plot highlights the predicted mean differences between N-back (N-B)/no N-back (No N-B) and time budget (TTC = 3 s/TTC = 5 s) alongside 50 % and 95 % credible interval bars. B) Posterior predictions of the expected RT_{HO} for each time budget. C) Marginal Effect at the Representative value (MER) of time budget on RT_{HO} ($MER_{RT_{HO}}$).

Table 3
Posterior means and 95% CIs for parameters predicting M_D.

Fixed effects	Dependent variable:	
	M_D	*pd*
β_0	−3.223 (−3.630, −2.827)	100 %
β_N	0.252 (−0.276, 0.768)	83.08 %
β_T	1.518 (1.148, 1.898)	100 %
β_{NT}	−0.163 (−0.672, 0.359)	73.68 %
Participants	37	
Observations	241	

control of the vehicle was more variable following a critical event with a TTC of 3 s. Once again, there was no consistent or substantial effects of MWL on lane position variability following the takeover.

3.3. Gaze behaviours

3.3.1. Model fitting

The standard deviation of horizontal gaze (SD_{YAW}) was calculated for a 30 s period before the takeover (i.e., during hands-off L2 driving) and a 30 s period following the takeover (i.e., during manual driving). The pre-takeover SD_{YAW} was positively skewed and thus was modelled via a Log-Normal distribution. A parameter modelling the effect of time budget was not necessary because the critical event had not unfolded and thus had no bearing on the drivers gaze behaviour. All pre-takeover data referred to trials with a lead vehicle, as these were the same trials where critical events took place. As such, the model was parameterised with parameters representing an intercept (β_0) and the influence of N-back (β_N):

$$Y_{ij}\ LogNormal\left(\mu_{ij},\sigma_{ij}\right)$$

$$\mu_{ij} = \left(\beta_0 + \beta_{0_j}\right) + \left(\beta_N N_i + \beta_{N_j} N_i\right)$$

$$\begin{bmatrix}\beta_{0_j}\\ \beta_{N_j}\end{bmatrix}\ MVN\left(\begin{bmatrix}\beta_0\\ \beta_N\end{bmatrix}, S_\beta\right)$$

$$S_\beta = \begin{pmatrix}\sigma^2_{\beta_{0_j}} & \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{0_j}}\\ \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{N_j}} & \sigma^2_{\beta_{N_j}}\end{pmatrix} \tag{4}$$

For post-takeover SD_{YAW}, the data were distributed more normally however initial modelling revealed that the model was predicting negative SD_{YAW} values on some occasions (see supplemental material (https://osf.io/e4rkj/overview) for more information on this). As SD_{YAW} is a measure of variation in eye movements, it cannot be negative and thus to combat this, it was a modelled with a truncated Normal distribution with the lower bound set as 0 ($a = 0$). Paramertisation for post-takeover gaze behaviours included an intercept (β_0), a parameter for the effect of N-back (when $N \in \{0,1\}$, β_N), a parameter for the effect of time budget (when $T \in \{0,1\}$, β_T), and the interaction term (NT, β_{NT}); this was the same as the post-takeover manual driving and response time models.

$$Y_{ij}\ Normal\left(\mu_{ij},\sigma_e,a,b\right)$$

$$\mu_{ij} = \left(\beta_0 + \beta_{0_j}\right) + \left(\beta_N N_i + \beta_{N_j} N_i\right) + \left(\beta_T T_i + \beta_{T_j} T_i\right) + \left(\beta_{NT} NT_i + \beta_{NT_j} NT_i\right)$$

$$\begin{bmatrix}\beta_{0_j}\\ \beta_{N_j}\\ \beta_{T_j}\\ \beta_{NT_j}\end{bmatrix}\ MVN\left(\begin{bmatrix}\beta_{0_j}\\ \beta_{N_j}\\ \beta_{T_j}\\ \beta_{NT_j}\end{bmatrix}, S_\beta\right)$$

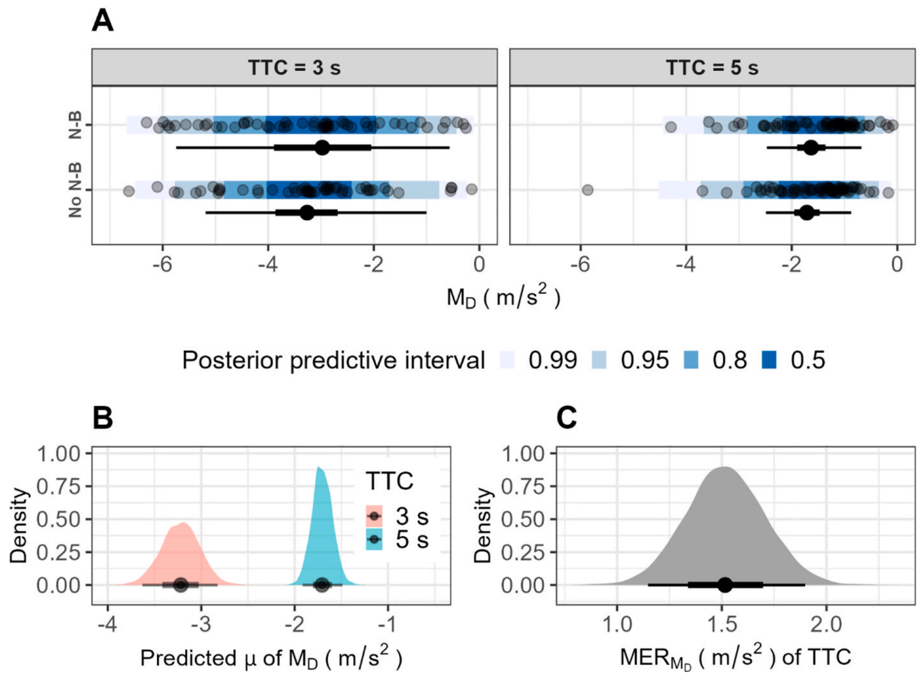

Fig. 6. A) Posterior predictive bands and posterior distribution of means plotted against raw data for M_D. The point-interval plot highlights the predicted mean differences between N-back (N-B)/no N-back (No N-B) and time budget (TTC = 3 s/TTC = 5 s) alongside 50 % and 95 % credible interval bars. B) Posterior predictions of the expected M_D for each time budget. C) Marginal Effect at the Representative value (MER) of time budget on M_D (MER_{M_D}).

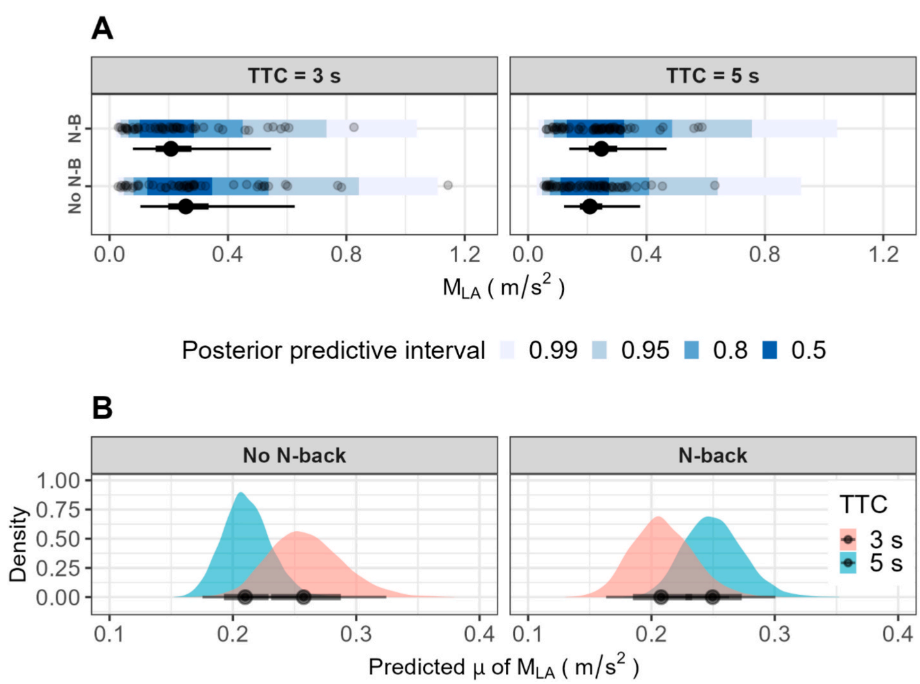

Fig. 7. A) Posterior predictive bands and posterior distribution of means plotted against raw data for M_{LA}. The point-interval plot highlights the predicted mean differences between N-back (N-B)/no N-back (No N-B) and time budget (TTC = 3 s/TTC = 5 s) alongside 50 % and 95 % credible interval bars. B) Posterior predictions of the expected M_{LA} within each time budget and N-back condition.

Table 4
Posterior means and 95% CIs for parameters predicting M_{LA}.

Fixed effects		
	Dependent variable:	
	M_{LA}	*pd*
β_0	−1.544 (−1.768, −1.321)	100 %
β_N	−0.215 (−0.470, 0.034)	95.32 %
β_C	−0.203 (−0.468, 0.057)	94.00 %
β_{NC}	0.387 (0.055, 0.718)	98.80 %
Participants	37	
Observations	241	

Table 5
Posterior means and 95% CIs for parameters predicting SD_{LP}.

Fixed effects		
	Dependent variable:	
	SD_{LP}	*pd*
β_0	−1.278 (−1.533, −1.021)	100 %
β_N	−0.038 (−0.336, 0.256)	60.85 %
β_C	−0.358 (−0.649, −0.076)	99.35 %
β_{NC}	0.068 (−0.441, 0.312)	63.75 %
Participants	37	
Observations	241	

$$S_\beta = \begin{pmatrix} \sigma^2_{\beta_{0_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{N_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{T_j}} & \rho\sigma_{\beta_{0_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{0_j}} & \sigma^2_{\beta_{N_j}} & \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{T_j}} & \rho\sigma_{\beta_{N_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{0_j}} & \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{N_j}} & \sigma^2_{\beta_{T_j}} & \rho\sigma_{\beta_{T_j}}\sigma_{\beta_{NT_j}} \\ \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{0_j}} & \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{N_j}} & \rho\sigma_{\beta_{NT_j}}\sigma_{\beta_{T_j}} & \sigma^2_{\beta_{NT_j}} \end{pmatrix} \quad (5)$$

3.3.2. Standard deviation of horizontal gaze (SD_{YAW}): Pre-takeover

Coefficient means and 95 % CIs are summarized in Table 6. The model predicted with high certainty that the dispersion in horizontal gaze was reduced when drivers were under high MWL during hands-off L2 driving. Predictions implied by the model parameters indicated that this effect was large; the standard deviation of horizontal gaze was more than 4° fewer ($MER_{SD_{YAW}}$ = -4.559, [CI: −6.117, −3.138]) under high MWL (5.438°) versus when only monitoring the road environment (9.998°). This analysis is highlighted in Fig. 9; contour plots show the average distribution of gaze during 30 s of hands-off L2 driving before a TOR when drivers were just monitoring the road (A) versus when they were completing the N-back task (B).

Fig. 9 highlights classic characteristics of visual tunneling. There was increased gaze concentration towards the location approximated to be the road centre, and there was a reduction in the dispersion of gaze across the horizontal axis. It should also be noted that there was less gaze concentration towards the approximate locations of the rear-view and wing mirrors during high MWL conditions. The culmination of these effects resulted in an overall reduction in SD_{YAW} under high MWL during hands-off L2 driving.

3.3.3. Standard deviation of horizontal gaze (SD_{YAW}): Post-takeover

Coefficient means and 95 % CIs are summarized in Table 7. The model predicted with relatively high certainty that the dispersion of horizontal gaze was lower during manual driving following takeovers with higher time budgets (TTC = 5 s) (SD_{YAW} = 9.642°) versus takeovers with smaller time budgets (TTC = 3 s) (SD_{YAW} = 10.552°) ($MER_{SD_{YAW}}$ = -0.909, [CI: −1.833, −0.007]) (see Fig. 10). The model parameters also suggested that MWL may have had some carry over effects on horizontal gaze dispersion, resulting in decreases in SD_{YAW} during manual driving periods that follow hands-off L2 driving during high MWL (SD_{YAW} =

Table 6
Posterior means and 95% CIs for parameters predicting SD_{YAW}.

Fixed effects		
	Dependent variable:	
	SD_{YAW}	*pd*
β_0	2.230 (2.088, 2.369)	100 %
β_N	−0.611 (−0.825, −0.408)	100 %
Participants	37	
Observations	241	

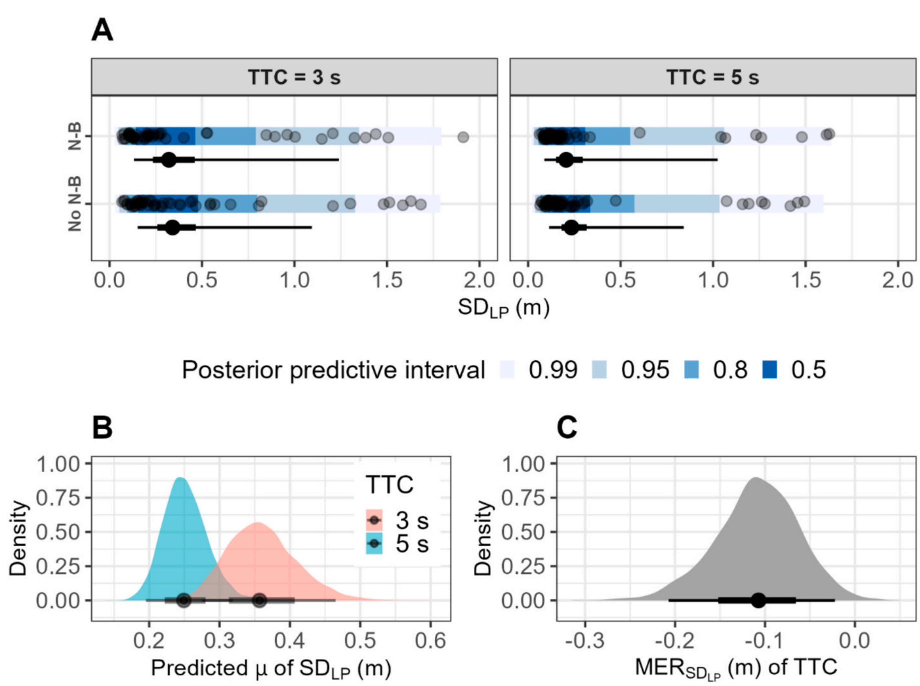

Fig. 8. Posterior predictive bands and posterior distribution of means plotted against raw data for SD_{LP}. The point-interval plot highlights the predicted mean differences between N-back (N-B)/no N-back (No N-B) and time budget (TTC = 3 s/TTC = 5 s) alongside 50 % and 95 % credible interval bars. B) Posterior predictions of the expected SD_{LP} for each event criticality. C) Marginal Effect at Representative value (MER) of time budget on SD_{LP} ($MER_{SD_{LP}}$).

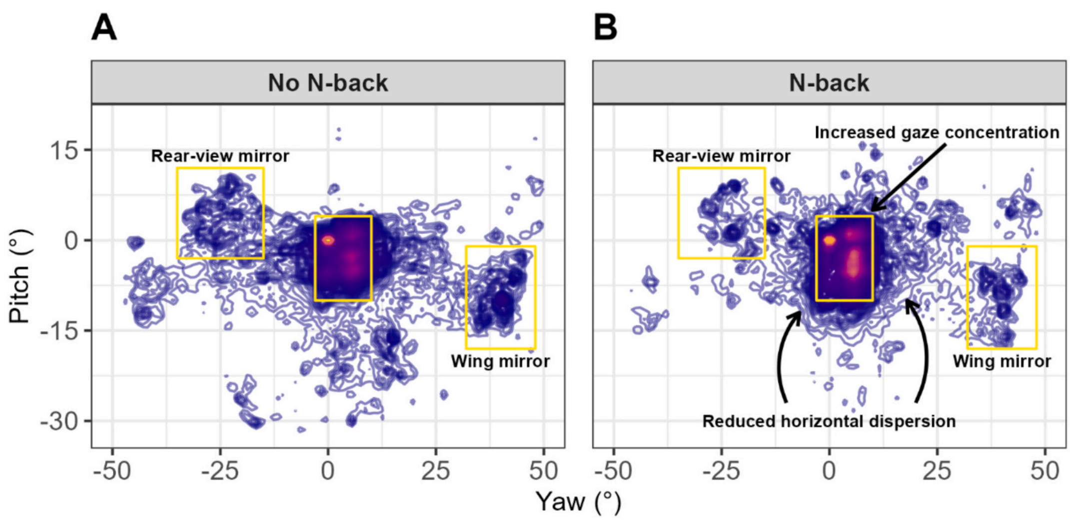

Fig. 9. Contour plots show the average distribution of gaze during hands-off L2 driving 30 s before a takeover event when monitoring the road (panel A) and when completing N-back (panel B). Yellow boxes highlight the approximate locations of the rear-view mirror, wing mirror, and the road centre. Average driver gaze was more concentrated towards the road centre with lower dispersion across the horizontal axis when drivers were under high MWL (see panel B). Gaze was also less concentrated towards rear-view and wing mirror locations during high MWL conditions. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 7
Posterior means and 95% CIs for parameters predicting SD_{YAW}.

Fixed effects		
	Dependent variable:	
	SD_{YAW}	*pd*
β_0	10.551 (9.586, 11.473)	100 %
β_N	−0.759 (−1.881, 0.391)	90.43 %
β_C	−0.911 (−1.831, 0.002)	97.53 %
β_{NC}	−0.142 (−1.456, 1.133)	57.95 %
Participants	37	
Observations	241	

9.793) versus monitoring the road environment (SD_{YAW} = 10.552) ($MER_{SD_{YAW}}$ = -0.758, [CI: −1.919, 0.337]). However, given the uncertainty associated with this estimation and the small size of the effect, it cannot be stated with reasonable confidence whether MWL produced positive or negative carryover effects in SD_{YAW} during post-takeover manual driving.

Fig. 11 shows a contour plot visually summarising the analysis conducted in Table 7. It highlights the average gaze distribution during 30 s of manual driving post-takeover in each of the four conditions. The distribution of gaze was slightly more constrained towards the approximate location of the road centre following events with larger time budgets (TTC = 5 s).

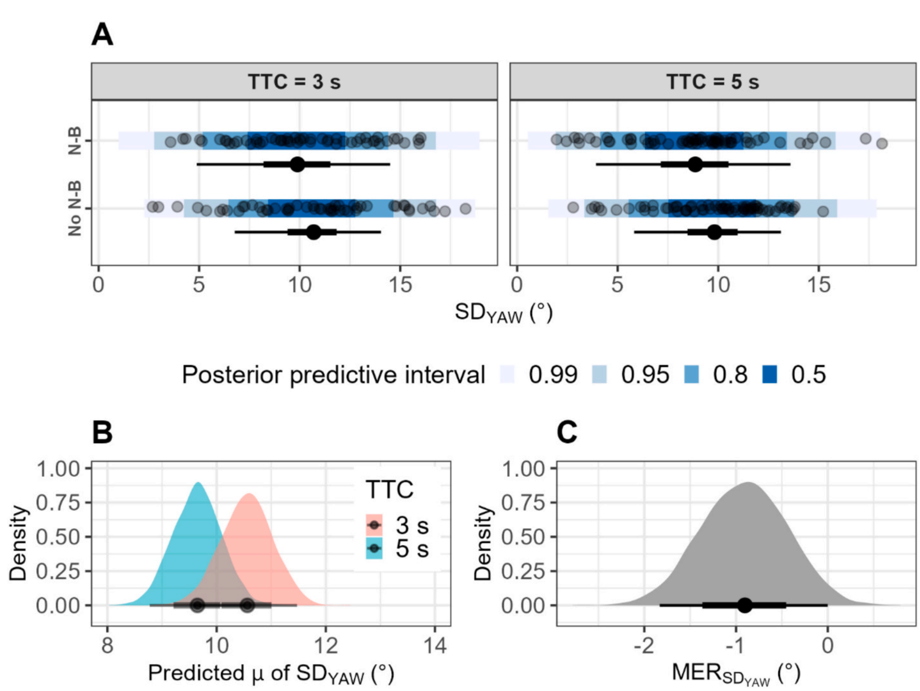

Fig. 10. Posterior predictive bands and posterior distribution of means plotted against raw data for SD_{YAW}. The point-interval plot highlights the predicted mean differences between N-back (N-B)/no N-back (No N-B) and time budget (TTC = 3 s/TTC = 5 s) alongside 50 % and 95 % credible interval bars. B) Posterior predictions of the expected SD_{YAW} for each event criticality. C) Marginal Effect at Representative value (MER) of time budget on SD_{YAW} ($MER_{SD_{YAW}}$).

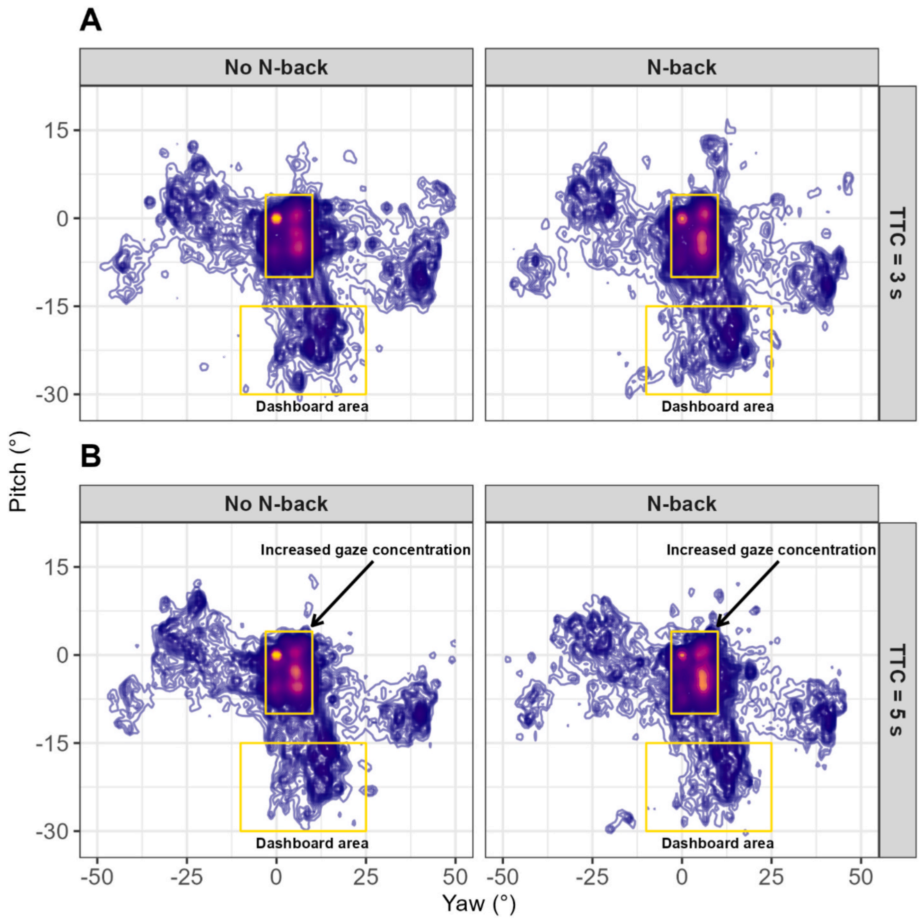

Fig. 11. Contour plots showing the average distribution of gaze during manual driving following each of the 4 conditions. Yellow boxes highlight the approximate locations of the road centre and the dashboard area. Average driver gaze was more concentrated towards the approximate road centre after a takeover event with a larger time budget (panel B). In all conditions, there was more gaze distribution towards the approximate location of the dashboard area than during automated driving. This was indicative of drivers checking the status of the automated system. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Despite the model parameters alluding to possible carryover effects of MWL-induced visual tunneling from automated to manual driving, this was not visually clear in the average gaze distribution plots in Fig. 11. One explanation for this disparity could be variability across the sample. It is possible that whilst some drivers exhibited carryover effects, other drivers did not, and thus the average gaze distribution plots highlight no evidence for it. A common heuristic used to judge the heterogeneity of an effect is the relative size of the random effect ($\sigma_{\beta_{N_j}}$) in relation to the fixed effect (β_N) of a multilevel model (Bolger et al, 2019). Bolger et al (2019) proposed that if the standard deviation of the effect was 0.25, or greater, of the average (fixed) effect, the variability of the effect may be worthy of note. For the post-takeover SD_{YAW} model, the relative size for the effect of MWL on SD_{YAW} was $\frac{\sigma_{\beta_{N_j}}}{\beta_N} = 2.32$. This indicated that variance in the effect of N-back on post-takeover SD_{YAW} was double the size of the average effect, which suggested a high level of variation for the effect of MWL on horizontal gaze dispersion during post-takeover manual driving.

This was further highlighted in the strip plot in Fig. 12A. Some drivers (highlighted red) had average reductions in SD_{YAW} in the region of 2°. Conversely other drivers (highlighted green) showed no differences in their horizontal gaze dispersion whether they were under high MWL during hands-off L2 driving, or not. The implications of these effects are highlighted in panels B and C in Fig. 12. The average gaze distribution of participants who demonstrated no carryover effects are similar during post-takeover manual driving, regardless of completing N-back or monitoring the road environment. Conversely, participants estimated to have strong carryover effects show indications of visual tunneling in post-takeover manual driving following hands-off L2 driving under high MWL.

Previous research has indicated that age-related impairments in top-down attentional control can predict between-participants variation in how MWL impacts gaze behaviour (Goodridge et al, 2024; Schieber & Gilland, 2008). We therefore investigated whether age predicted variability in the visual tunnelling carryover effects demonstrated in Fig. 12. The model revealed that age accounted for 10 % of the between-participants variability in the effect of N-back on SD_{YAW} following a takeover (see Fig. 13). This implies that older than average drivers were more likely to have carryover effects attributed to MWL.

4. Discussion

This study aimed to investigate whether MWL and the time budget of a rear-end scenario influenced the timing and quality of takeover performance, and whether these factors influenced gaze behaviours during post-takeover manual control. In general, the time budget of the situation had the largest impact on the timing and quality of takeovers. Takeovers were faster, and post-takeover manual driving performance was more erratic, following events with smaller time budgets. N-back-induced MWL did not have strong effects on takeover performance. There was potential evidence of carryover effects of MWL on eye movements during the manual drive following a takeover; the model

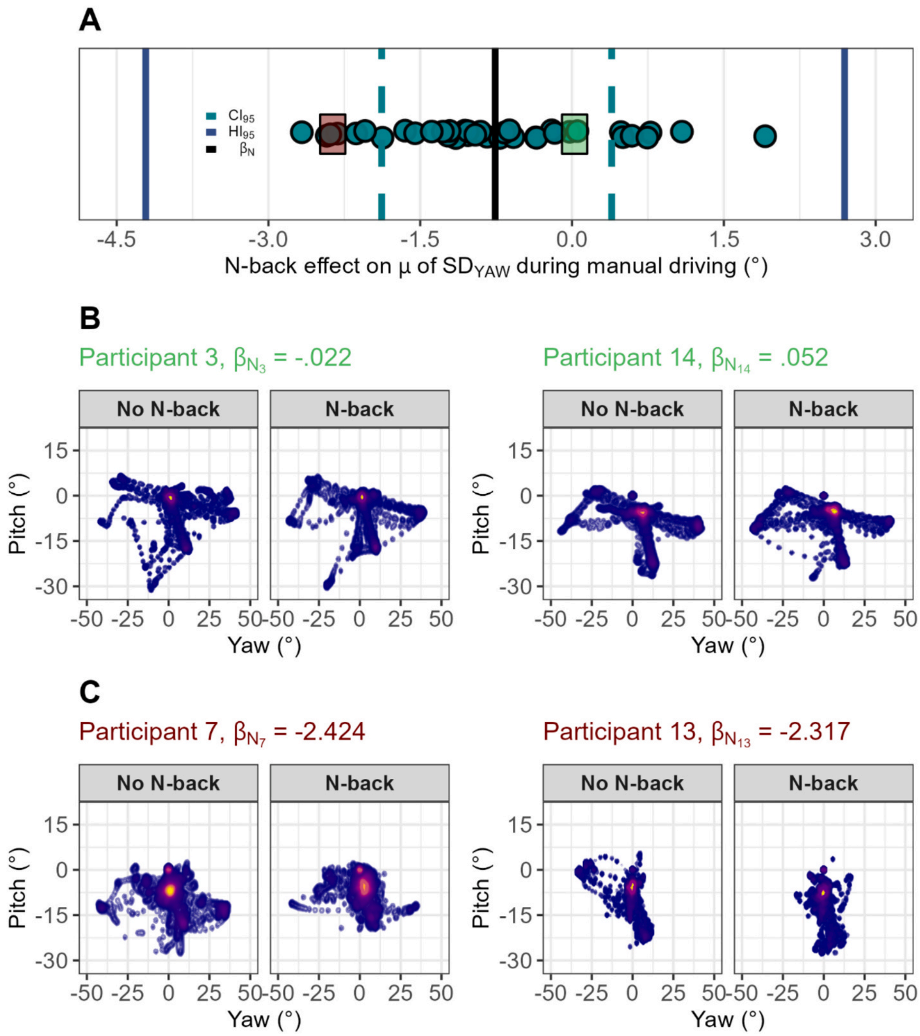

Fig. 12. A) Strip plot displaying the individual participant effects of N-back on SD_{YAW}. The black line denotes the average decrease in SD_{YAW} (fixed effect), the green dashed lines denote the heterogeneity of the average effect of N-back (95% Credible Intervals) and the blue solid lines denote the population heterogeneity of the effect of N-back. The red shaded annotation highlights participants who demonstrated carryover effects of MWL; the green shaded annotation highlights participants whose gaze was similar during manual driving regardless of MWL. B) Contour plots of the average gaze distribution for participants highlighted in green in panel A (demonstrating minimal carryover effects of reduced SD_{YAW}). Regardless of whether N-back was performed during hands-off L2 driving, the distribution of gaze during manual driving was very similar. C) Contour plots of the average gaze distribution for participants highlighted in red in panel A (demonstrating carryover effects of reduced SD_{YAW}). These participants had reduced horizontal dispersion of gaze during manual driving following trials where they completed the N-back during hands-off L2 driving. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

predicted a 90 % probability that horizontal gaze dispersion decreased during manual driving following high MWL during hands-off L2 driving. However, given the uncertainty associated with the estimate, neither the direction of this effect, nor it's magnitude, can be stated with any reasonable certainty. Except for a small interaction effect between MWL and time budgets on mean lateral accelerations, the remaining timing (RT_B, RT_{HO}), lateral (SD_{LP}), and longitudinal (M_D) measures of takeover quality revealed no statistical effects of MWL, supporting previous research in the area (Choi et al, 2020; Du et al, 2020; Mok et al, 2015; Wan & Wu, 2018; Wu et al, 2019).

The interaction effect between MWL and time budget on mean lateral accelerations implied that when time budgets were small (TTC = 3 s), drivers under high MWL produced less aggressive steering responses. Conversely, when time budgets were large (TTC = 5 s) drivers under high MWL produced more aggressive steering responses. An interesting aspect to this result was that the interaction was *dis-ordinal*, whereby the effect of one independent variable (MWL) on mean lateral acceleration was reversed based on the levels of the other independent variable (time budget). One explanation for this could be that whilst drivers had more time to respond when time budgets were longer, their increased MWL delayed the reallocation of cognitive resources towards decision making regarding their response. Consequently, drivers had to produce more erratic steering to avoid a potential collision. When time budgets were smaller, a driver who was monitoring the road (and thus potentially had more cognitive resources available for decision making) may have tried to immediately avoid a collision. In doing so, these drivers may have produced more aggressive steering manoeuvres whereas drivers under high MWL may have been content with only braking to reduce the imminent danger of the lead vehicle. Building on from this proposal, it might be possible that a combination of a small time budget and high MWL made drivers more aware of being out of the loop and thus less likely to attempt an evasive (and potentially more dangerous) steering response that, in turn, would produce higher mean lateral accelerations. Choi et al (2020) found evidence that drivers who reported higher subjective MWL produced more optimal takeover responses in critical situations, implying that a driver's awareness of being under high MWL resulted in more anticipatory responses.

The principal prediction of the CCH is that high MWL selectively

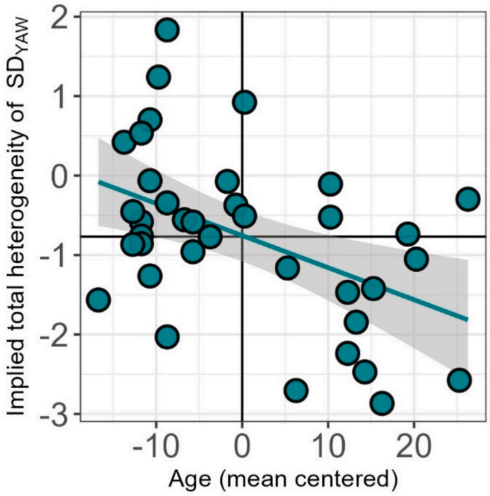

Fig. 13. Relationship between the implied total heterogeneity of SD_{YAW} and mean centred age. The x axis vertical line denotes mean age, y axis horizontal line denotes the average effect of N-back.

impairs driving subtasks that rely upon cognitive control leaving automatised performance unaffected (Engström et al., 2017a,b). Whether this hypothesis applies to takeover performance and more generally, automated driving, is an open question. However, the CCH may be a useful framework for understanding why high MWL did not negatively impact the timing or quality of takeovers in the current experiment. Braking in response to rear-end conflicts may be deemed automatised; the CCH would therefore predict that performance would be unaffected by MWL. The automatised nature of rear-end conflict responses derives from the strong neural pathways that detect looming. The visual system of insects (Peron & Gabbiani, 2009), avians (Sun & Frost, 1998; Wu et al, 2005), and mammals (Wu et al, 2005) is primed to detect looming. The subcortical structures involved in this process facilitate the modulation of motor and visual processing that inform rapid responses to this potentially threatening stimulus (Billington et al., 2011). Rear-end conflicts produce strong looming signals from the lead vehicle (Markkula et al, 2016), hence the higher cognitive functionalities that N-back aims to load may not be required for the comparatively simpler response of avoiding a looming lead vehicle. In this sense, the impact of MWL found in this study may not reflect or generalise to takeover scenarios that require more complex cognitive control, such as decision making in dense traffic or complex lane changes. If the CCH is indeed transferable to takeover performance, one prediction would be that higher MWL should negatively impact takeover behaviours that rely upon cognitive control. For example, the decision-making elements involved in commanded lane changes are said to rely on cognitive control because changing to a specified lane based on roadside commands is a non-practiced task (Engström et al., 2017a,b). It stands to reason that commands to change lane following periods of system monitoring, in addition to drivers being out-of-the-loop (Mole et al 2019; Merat et al 2019), may similarly be non-practiced and thus susceptible to poor performance under high MWL.

Another factor to consider when understanding the impact of high MWL is the nature of the tasks used to manipulate driver workload. Researchers have often used a range of tasks to load drivers during manual and automated driving (Goodridge et al, 2023). These are often artificial surrogate tasks that are considered to impose similar demands on drivers as hands-free phone conversations yet are standardised and easy to quantify in terms of performance. These include the N-back task (Mehler et al., 2011), the Sustained Attention Response Task (SART) (Hawkins et al, 2019), the Paced Auditory Serial Addition Task (PASAT) (Crawford et al, 1998), and the Twenty-Questions Task (TWT) (Merat et al, 2012; Siegler, 1977). The N-back in particular has been proposed as a suitable task for inducing high load; a recent *meta*-analysis concluded that the N-back produced moderate effect sizes in terms of physiological and subjective measures of MWL (von Janczewski et al, 2021). However, it is uncommon for researchers to discuss the ecological validity of these tasks. For example, are these WM tasks really equivalent to hands-free phone conversations? Strayer et al (2015) found that there were clear differences in MWL between common in-vehicle activities (i.e., listening to the radio, hands-free phone use) and WM tasks (i.e., Operation Span (OSPAN) task) as measured by subjective, behavioural, and neurophysiological measures. Whilst Strayer et al (2015) focused on manual driving, it does highlight that the level of induced workload is dependent on the task used. Another thing to consider is the difficulty of the NDRT that induces MWL. The current investigation only focused on two levels of manipulation (no task versus 2-back). However, it may be worthwhile investigating whether variations of the N-back task are more/less similar to common in-vehicle activities in terms of how much workload they induce. A benefit of the N-back is that manipulating N systemically manipulates the load; and in the case of manual driving, systematically impairs driving performance (He et al, 2019; Scheunemann et al, 2019; Stojmenova et al, 2017). Future research may want to understand which levels of the artificial standardised tasks (e.g., N-back) relate to in-vehicle tasks in terms of MWL induced, and impact on driver performance.

Whilst MWL had no influence on takeover reaction times, event criticality heavily influenced the speed of driver reactions. An average difference in brake reaction time of .13 s between severe (3 s) and less severe TTCs (5 s) translates into an extra 4 m before the brake was applied when travelling at 70 MPH. Furthermore, the upper bounds of the model's credible interval indicates that the effect could be even higher, resulting in drivers travelling an extra 7.76 m before brakes were applied, demonstrating the practical relevance of this modelling. Whilst previous studies have found larger effects of time budget on takeover time, these *meta*-analyses have focused on an amalgamation of Levels 2–4 (McDonald et al, 2019). The inclusion of higher automation levels likely inflates the influence of time budget as there is less (or no) onus on the driver to visually monitor the road environment. In general, the current findings support previous research highlighting that reaction times (specifically brake reaction times) in response to rear-end emergencies are strongly determined by the environmental context such as visual looming and the kinematics of the situation (Markkula et al, 2016).

The reduction in horizontal gaze dispersion as a function of MWL during hands-off L2 driving was very high – an average reduction of over 4° in the SD_{YAW} relative to monitoring the road. This is double the size of effects found in manual driving (Reimer, 2009; 2012). One explanation for this could be that driver gaze tends to be more dispersed during automated driving (Louw & Merat, 2017) which resulted in a larger reduction in gaze dispersion when under high load. A useful takeaway for DMS designers is the pattern of SD_{YAW} following a takeover. The model of post-takeover SD_{YAW} predicted a 90 % probability that gaze concentration continued to be constrained during manual driving following driver engagement with a MWL task during hands-off L2 driving. Some of the plausible parameter values for the carryover effect include reductions of SD_{YAW} up to 2°; this is a similar magnitude to previous research on the effects of MWL relative to no-load during manual driving (Reimer, 2009; 2012). The heterogeneity intervals imply that some drivers in the population could have carryover effects of up to 4° reductions in SD_{YAW} following high MWL during partially automated driving periods. This indicates that MWL on driver state may carry over to post-transition manual control, however some factors must be considered. Firstly, the group level effects implied by the model indicated that the effect of MWL on post-transition SD_{YAW} were very variable. Whilst heterogeneity intervals predicted that some drivers would have strong carryover effects, the intervals also implied that some drivers would demonstrate no carryover effects at all. An analysis of the implied random effects from the post-transition SD_{YAW} model revealed that age predicted 10 % of the between-participants variability in the effect of MWL on SD_{YAW}. This supports our previous research (Goodridge et al, 2024) where we found that age predicted the variability in the effect that MWL had on the dispersion and randomness of gaze transitions during hands-off L2 driving. Furthermore, despite this potential carryover effect, MWL did not substantially influence post-takeover driving performance. Therefore, empirical tests still need to establish whether changes in eye movements caused by high MWL have longer-lasting effects on driving performance following takeovers, especially when considering the current study only used 30 s of manual driving data.

One thing to note about the current result is the focus on driver behaviour and transitions of control when using and transitioning from *hands-off* L2 systems despite many L2 systems currently available on the market being *hands-on*. This could be framed as a limitation of the generalisability of the work, given the regulatory misalignment. However, there has been a lot of recent interest in exploring hands-off L2 systems from car manufacturers. For example, the United Kingdom (UK) recently approved Ford's BlueCruise system, which allows drivers to remove their hands from the steering wheel on pre-specified sections of the UK motorway network (ETSC, 2023). Mercedes recently showcased a prototype of an "L2++" system during an IAA auto show. Whilst "L2++" falls outside of the official SAE classification, the industry consensus is that it will involve hands-off capabilities and automatic lane changes (Gibbs, 2025). Hence the results from this study help inform our understanding of driver state and DMS requirements for future automation systems that are currently in development or have been approved for public roads.

A strength of this work is that the modelling technique used takes into account the distribution of the response variables, which allows for improved model fits and improved predictions of driver takeover responses. A specific example of this is the Shifted Log Normal distribution for response times. This distribution included a shift parameter (δ) that effectively modeled "non-decision time" of takeovers. Non-decision time refers to time taken up by processes such as perceptual encoding and motor coordination (Evans & Wagenmakers, 2019). The model developed in this manuscript provides an additional step of mechanistic plausibility when using statistical models to understand takeover behaviours. The inclusion of a latent parameter that models non-decision time allows for the decomposition of the decision-making process (Mulder & van Maanen, 2013). As such, researchers can assess changes in the underlying cognitive processes that contribute towards a response, rather than indirectly inferring changes via raw variables such as mean response time (Evans & Wagenmakers, 2019). However, the current manuscript only modelled non-decision time for the overall distribution of hands-on time ($\delta = 0.462$) and brake reaction time ($\delta = 0.457$). At the very least, future research might want to investigate the extent to which non-decision time varies within the population, and/or whether MWL and time budget influence the non-decision time during the takeover process. Such an analysis would be particularly beneficial for research designs that involve a decision-making process rather than automatised responses to looming rear-end scenarios. For example, paradigms that focus on lane changes or hazard perception and thus require the driver to make critical decisions based on the predicted movements of other road users. As mentioned above, these behaviours may rely more on cognitive control and thus are potentially more likely to be susceptible to the loading of cognitive resources.

A potential limitation of the current work might be the perceived unrealistic nature of the traffic conflict. For example, vehicles on the market today with L2 functionality also have Forward Collision Warning (FCW) and Automatic Emergency Braking (AEB) capabilities to address rear-end conflicts. According to Euro NCAP, car-to-car rear impacts are among the most frequent types of road accidents, often resulting from driver distraction or misjudgement. The current study selected a car-to-car rear moving (CCRm) scenario; a critical test scenario used by Euro NCAP to evaluate the performance of FCW and AEB systems (EURO NCAP, 2023). However, to focus on assessing driver reactions, these assistance systems were excluded from the driving scenario. Typically, FCW activates at 3 to 3.5 s time-to-collision (TTC), which would interfere with our test parameters. Furthermore, the inclusion of FCW and AEB would not contribute additional value, as the primary objective of this study was to measure driver reaction time and takeover performance at early stages.

In conclusion, results from this study suggest that time budget, not N-back induced MWL, influenced takeover performance. Drivers were faster to react when time budgets were small, but their post-takeover manual control of the vehicle was more variable. MWL had no effect on takeover timing or performance, which may be due to the scenario used. In other words, the rear-end critical event has a simple response remit: which is to brake quickly and heavily. Therefore, an overtaking scenario might be better for testing the detrimental effects of MWL on decision making tasks in driving, given the shifting of attentional resources required for a lane change manoeuvre (Gonçalves et al, 2019; Mourant & Rockwell, 1971; Underwood et al 2003). This study provided some evidence of carryover effects in terms of gaze behaviour, however, future research will need to investigate this further, over longer periods of time.

CRediT authorship contribution statement

Courtney M. Goodridge: . **Rafael C. Gonçalves:** Writing – review & editing, Methodology, Investigation, Data curation. **Ali Arabian:** Investigation, Data curation. **Anthony Horrobin:** Software. **Albert Solernou:** Supervision, Software, Project administration. **Yee Thung Lee:** Investigation, Data curation. **Audrey Bruneau:** Writing – review & editing, Writing – original draft, Methodology, Conceptualization. **Yee Mun Lee:** Methodology, Conceptualization. **Natasha Merat:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

Acknowledgements

The authors would like to thank all partners within the Hi-Drive project for their cooperation and valuable contribution. [This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101006664. The sole responsibility of this publication lies with the authors. Neither the European Commission nor CINEA – in its capacity of Granting Authority – can be made responsible for any use that may be made of the information this document contains]. We would like to thank Seeing Machines for the use of their eye tracking equipment to collect data for this study and Michael Daly for software development. We would also like to thank Giancarlo Caccia Dominioni for their insightful comments for the design, analysis, and writing of this manuscript.

Data availability

Data and analysis code are available in the link stated in the manuscript.

References

Billington, J., Wilkie, R.M., Field, D.T., Wann, J.P., 2011. Neural processing of imminent collision in humans. Proc. R. Soc. B Biol. Sci. 278 (1711), 1476–1481.

Biondi, F.N., Jajo, N., 2024. On the impact of on-road partially-automated driving on drivers' cognitive workload and attention allocation. Accid. Anal. Prev. 200, 107537.

Bolger, N., Zee, K.S., Rossignac-Milon, M., Hassin, R.R., 2019. Causal processes in psychology are heterogeneous. J. Exp. Psychol. Gen. 148 (4), 601.
Bürkner, P.C., 2017. brms: an R package for Bayesian multilevel models using Stan. J. Stat. Softw. 80, 1–28.
Carsten, O., Lai, F.C., Barnard, Y., Jamson, A.H., Merat, N., 2012. Control task substitution in semiautomated driving: does it matter what aspects are automated? Hum. Factors 54 (5), 747–761.
Choi, D., Sato, T., Ando, T., Abe, T., Akamatsu, M., Kitazaki, S., 2020. Effects of cognitive and visual loads on driving performance after take-over request (TOR) in automated driving. Appl. Ergon. 85, 103074.
Crawford, J.R., Obonsawin, M.C., Allan, K.M., 1998. PASAT and components of WAIS-R performance: Convergent and discriminant validity. Neuropsychol. Rehabil. 8 (3), 255–272.
Cumming, G., 2014. The new statistics: why and how. Psychol. Sci. 25 (1), 7–29.
De Waard, D. (1996). The measurement of drivers' mental workload.
Deniel, J., Navarro, J., 2023. Gaze behaviours engaged while taking over automated driving: a systematic literature review. Theor. Issues Ergon. Sci. 24 (1), 54–87.
Du, N., Kim, J., Zhou, F., Pulver, E., Tilbury, D.M., Robert, L.P., Yang, X.J., 2020a. September). evaluating effects of cognitive load, takeover request lead time, and traffic density on drivers' takeover performance in conditionally automated driving. In: In *12th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, pp. 66–73.
Du, N., Yang, X.J., Zhou, F., 2020b. Psychophysiological responses to takeover requests in conditionally automated driving. Accid. Anal. Prev. 148, 105804.
Engström, J., 2011. *Understanding attention selection in driving: from limited capacity to adaptive behaviour*. Chalmers Tekniska Hogskola (sweden).
Engström, J., Markkula, G., & Merat, N. (2017, March). Modeling the effect of cognitive load on driver reactions to a braking lead vehicle: A computational account of the cognitive control hypothesis. In *5th International Conference of Driver Distraction and Inattention, Paris, France*.
Engström, J., Markkula, G., Victor, T., Merat, N., 2017b. Effects of cognitive load on driving performance: the cognitive control hypothesis. Hum. Factors 59 (5), 734–764.
EURO NCAP (2023) Assisted driving highway assist systems. Available in https://www.euroncap.com/media/79864/euro-ncap-aeb-c2c-test-protocol-v43.pdf Accessed 09 Apr 2025.
European Transport Safety Council (ETSC). (2023, April 16). UK permits hands-off Level 2 driver assistance system. https://etsc.eu/uk-permits-hands-off-level-2-driver-assistance-system/.
Evans, N.J., Wagenmakers, E.J., 2019. Theoretically meaningful models can answer clinically relevant questions. Brain 142 (5), 1172–1175.
Gibbs, N. (2025, October 2). How BMW, Mercedes, others aim to make supervised hands-off driving more attainable. https://autos.yahoo.com/ev-and-future-tech/articles/bmw-mercedes-others-aim-supervised-122638152.html?guccounter=1&guce_referrer=aHR0cHM6Ly93d3cuZ29vZ2xlLmNvbS8&guce_referrer_sig=AQAAADqgmn3zl2a3y7wk0wsrO6L0BIkKX2T3Wr0ppqJbRyM2P9SllkHhswQJBuz8Viuxq7Myyb-xNg7bTuQVglOLSZx_PGyWbO5fhSbmaNGjdOROK3gxJl0WzAI5F_-aSr8C4HY7f_2Ripz_veJLKc8HTsNQtgSxY1OX5iBI7Q1jTpjS.
Gold, C., Berisha, I., & Bengler, K. (2015, September). Utilization of drivetime–performing non-driving related tasks while driving highly automated. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 59, No. 1, pp. 1666-1670). Sage CA: Los Angeles, CA: SAGE Publications.
Gold, C., Damböck, D., Lorenz, L., & Bengler, K. (2013, September). "Take over!" How long does it take to get the driver back into the loop?. In Proceedings of the human factors and ergonomics society annual meeting (Vol. 57, No. 1, pp. 1938-1942). Sage CA: Los Angeles, CA: Sage Publications.
Gold, C., Happee, R., Bengler, K., 2018. Modeling take-over performance in level 3 conditionally automated vehicles. Accid. Anal. Prev. 116, 3–13.
Gold, C., Körber, M., Lechner, D., Bengler, K., 2016. Taking over control from highly automated vehicles in complex traffic situations: the role of traffic density. Hum. Factors 58 (4), 642–652.
Gonçalves, R. C., Goodridge, C. M., Kuo, J., Lenné, M. G., & Merat, N. (2024). Using driver monitoring to estimate readiness in automation: A conceptual model based on simulator experimental data.
Goncalves, R.C., Louw, T.L., Madigan, R., Quaresma, M., Romano, R., Merat, N., 2022. The effect of information from dash-based human-machine interfaces on drivers' gaze patterns and lane-change manoeuvres after conditionally automated driving. Accid. Anal. Prev. 174, 106726.
Gonçalves, R., Louw, T., Madigan, R., & Merat, N. (2019, June). Using Markov chains to understand the sequence of drivers' gaze transitions during lane-changes in automated driving. In *Driving Assessment Conference* (Vol. 10, No. 2019). University of Iowa.
Goodridge, C.M., Gonçalves, R.C., Öztürk, İ., 2023. What do we mean by cognitive load? Towards more accurate definition of the term for better identification by driver monitoring systems. In: In *Adjunct Proceedings of the 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, pp. 256–259.
Goodridge, C.M., Goncalves, R.C., Arabian, A., Horrobin, A., Solernou, A., Lee, Y.T., Merat, N., 2024. Gaze entropy metrics for mental workload estimation are heterogenous during hands-off level 2 automation. Accid. Anal. Prev. 202, 107560.
Hawkins, G.E., Mittner, M., Forstmann, B.U., Heathcote, A., 2019. Modeling distracted performance. Cogn. Psychol. 112, 48–80.
He, D., Donmez, B., Liu, C.C., Plataniotis, K.N., 2019. High cognitive load assessment in drivers through wireless electroencephalography and the validation of a modified N-back task. IEEE Trans. Hum.-Mach. Syst. 49 (4), 362–371.
Hecht, T., Feldhütter, A., Radlmayr, J., Nakano, Y., Miki, Y., Henle, C., & Bengler, K. (2019). A review of driver state monitoring systems in the context of automated driving. In *Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018) Volume VI: Transport Ergonomics and Human Factors (TEHF), Aerospace Human Factors and Ergonomics 20* (pp. 398-408). Springer International Publishing.
Heiss, A., 2022. Marginalia: A guide to figuring out what the heck marginal effects, marginal slopes, average marginal effects, marginal effects at the mean, and all these other marginal things are. *Andrew Heiss*.
Hyde, S., 2018. *The Influence of Vehicle Automation on Visual Attention and Situation Awareness*. Royal Holloway, University of London). Doctoral dissertation.
Kim, J., Kim, W., Kim, H.S., Lee, S.J., Kwon, O.C., Yoon, D., 2022. A novel study on subjective driver readiness in terms of non-driving related tasks and take-over performance. ICT Express 8 (1), 91–96.
Lazic, S.E., 2010. The problem of pseudoreplication in neuroscientific studies: is it affecting your analysis? BMC Neurosci. 11, 1–17.
Lindeløv, J. K., 2019. Reaction Time Distributions-An Interactive Overview.
Louw, T., Merat, N., 2017. Are you in the loop? using gaze dispersion to understand driver visual attention during vehicle automation. Transp. Res. Part C Emerging Technol. 76, 35–50.
Louw, T., Kountouriotis, G., Carsten, O., & Merat, N. (2015). Driver inattention during vehicle automation: How does driver engagement affect resumption of control?. In 4th International Conference on Driver Distraction and Inattention (DDI2015), Sydney: proceedings. ARRB Group.
Louw, T., Madigan, R., Carsten, O., Merat, N., 2017. Were they in the loop during automated driving? Links between visual attention and crash potential. Inj. Prev. 23 (4), 281–286.
Marberger, C., Mielenz, H., Naujoks, F., Radlmayr, J., Bengler, K., & Wandtner, B. (2018). Understanding and applying the concept of "driver availability" in automated driving. In *Advances in Human Aspects of Transportation: Proceedings of the AHFE 2017 International Conference on Human Factors in Transportation, July 17− 21, 2017, The Westin Bonaventure Hotel, Los Angeles, California, USA 8* (pp. 595-605). Springer International Publishing.
Marberger, C., Mielenz, H., Naujoks, F., Radlmayr, J., Bengler, K., & Wandtner, B. (2018). Understanding and applying the concept of "driver availability" in automated driving. In *Advances in Human Aspects of Transportation: Proceedings of the AHFE 2017 International Conference on Human Factors in Transportation, July 17− 21, 2017, The Westin Bonaventure Hotel, Los Angeles, California, USA 8* (pp. 595-605). Springer International Publishing.
Markkula, G., Engström, J., Lodin, J., Bärgman, J., Victor, T., 2016. A farewell to brake reaction times? kinematics-dependent brake response in naturalistic rear-end emergencies. Accid. Anal. Prev. 95, 209–226.
McDonald, A.D., Alambeigi, H., Engström, J., Markkula, G., Vogelpohl, T., Dunne, J., Yuma, N., 2019. Toward computational simulations of behavior during automated driving takeovers: a review of the empirical and modeling literatures. Hum. Factors 61 (4), 642–688.
Mehler, B., Reimer, B., Dusek, J.A., 2011. MIT AgeLab delayed digit recall task (n-back), 17. Institute of Technology, Cambridge, MA: Massachusetts, p. 33.
Melnicuk, V., Thompson, S., Jennings, P., Birrell, S., 2021. Effect of cognitive load on drivers' state and task performance during automated driving: introducing a novel method for determining stabilisation time following take-over of control. Accid. Anal. Prev. 151, 105967.
Merat, N., Jamson, A.H., Lai, F.C., Carsten, O., 2012. Highly automated driving, secondary task performance, and driver state. Hum. Factors 54 (5), 762–771.
Merat, N., Jamson, A.H., Lai, F.C., Daly, M., Carsten, O.M., 2014. Transition to manual: driver behaviour when resuming control from a highly automated vehicle. Transport. Res. F: Traffic Psychol. Behav. 27, 274–282.
Merat, N., Seppelt, B., Louw, T., Engström, J., Lee, J.D., Johansson, E., Keinath, A., 2019. The "Out-of-the-Loop" concept in automated driving: proposed definition, measures and implications. Cogn. Tech. Work 21, 87–98.
Mioch, T., Kroon, L., & Neerincx, M. A. (2017, March). Driver readiness model for regulating the transfer from automation to human control. In *Proceedings of the 22nd international conference on intelligent user interfaces* (pp. 205-213).
Mok, B. K. J., Johns, M., Lee, K. J., Ive, H. P., Miller, D., & Ju, W. (2015, June). Timing of unstructured transitions of control in automated driving. In *2015 IEEE intelligent vehicles symposium (IV)* (pp. 1167-1172). IEEE.
Mok, B., Johns, M., Lee, K. J., Miller, D., Sirkin, D., Ive, P., & Ju, W. (2015, September). Emergency, automation off: Unstructured transition timing for distracted drivers of automated vehicles. In *2015 IEEE 18th international conference on intelligent transportation systems* (pp. 2458-2464). IEEE.
Mole, C.D., Lappi, O., Giles, O., Markkula, G., Mars, F., Wilkie, R.M., 2019. Getting back into the loop: the perceptual-motor determinants of successful transitions out of automated driving. Hum. Factors 61 (7), 1037–1065.
Mourant, R. R., Rockwell, T. H., 1971. Visual scan patterns of novice and experienced drivers.
Mueller, A.S., Cicchino, J.B., Calvanelli Jr, J.V., 2024. Habits, attitudes, and expectations of regular users of partial driving automation systems. J. Saf. Res. 88, 125–134.
Mulder, M.J., van Maanen, L., 2013. Are accuracy and reaction time affected via different processes? PLoS One 8 (11), e80222.
Nguyen, M. (2023). A guide on data analysis.
Pan, H., He, H., Wang, Y., Cheng, Y., Dai, Z., 2023. The impact of non-driving related tasks on the development of driver sleepiness and takeover performances in prolonged automated driving. J. Saf. Res. 86, 148–163.
Pan, H., Payre, W., Wang, Y., Gao, Z., 2025. How do visual and cognitive non-driving related tasks affect drivers' visual attention and takeover performance in conditionally automated driving? J. Transport. Safety Security 17 (1), 97–123.

Parasuraman, R., Byrne, E.A., 2003. Automation and human performance in aviation. Principles and Practice of Aviation Psychology 311–356.

Parasuraman, R., Molloy, R., Singh, I.L., 1993. Performance consequences of automation-induced'complacency'. Int. J. Aviat. Psychol. 3 (1), 1–23.

Parasuraman, R., Mouloua, M., Molloy, R., Hilburn, B., 2018. Monitoring of automated systems. In: *Automation and Human Performance*. CRC Press, pp. 91–115.

Peron, S., Gabbiani, F., 2009. Spike frequency adaptation mediates looming stimulus selectivity in a collision-detecting neuron. Nat. Neurosci. 12 (3), 318–326.

Perraillon, M.C., 2019. Interpreting Model Estimates: Marginal Effects. University of Colorado Anschutz Medical Campus, Nova School of Business and Economics Lisbon, Portugal.

Radlmayr, J., Fischer, F. M., & Bengler, K. (2019). The influence of non-driving related tasks on driver availability in the context of conditionally automated driving. In *Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018) Volume VI: Transport Ergonomics and Human Factors (TEHF), Aerospace Human Factors and Ergonomics 20* (pp. 295-304). Springer International Publishing.

Radlmayr, J., Gold, C., Lorenz, L., Farid, M., & Bengler, K. (2014, September). How traffic situations and non-driving related tasks affect the take-over quality in highly automated driving. In Proceedings of the human factors and ergonomics society annual meeting (Vol. 58, No. 1, pp. 2063-2067). Sage CA: Los Angeles, CA: Sage Publications.

Reimer, B., 2009. Impact of cognitive task complexity on drivers' visual tunneling. Transp. Res. Rec. 2138 (1), 13–19.

Reimer, B., Mehler, B., Wang, Y., & Coughlin, J. F. (2010, September). The impact of systematic variation of cognitive demand on drivers' visual attention across multiple age groups. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (Vol. 54, No. 24, pp. 2052-2055). Sage CA: Los Angeles, CA: SAGE Publications.

Reimer, B., Mehler, B., Wang, Y., Coughlin, J.F., 2012. A field study on the impact of variations in short-term memory demands on drivers' visual attention and driving performance across three age groups. Hum. Factors 54 (3), 454–468.

Samani, A.R., Mishra, S., Dey, K., 2022. Assessing the effect of long-automated driving operation, repeated take-over requests, and driver's characteristics on commercial motor vehicle drivers' driving behavior and reaction time in highly automated vehicles. Transport. Res. F: Traffic Psychol. Behav. 84, 239–261.

Siegler, R.S., 1977. The twenty questions game as a form of problem solving. Child Dev. 395–403.

Sodhi, M., Reimer, B., Llamazares, I., 2002. Glance analysis of driver eye movements to evaluate distraction. Behav. Res. Methods Instrum. Comput. 34, 529–538.

Stojmenova, K., Jakus, G., Sodnik, J., 2017. Sensitivity evaluation of the visual, tactile, and auditory detection response task method while driving. Traffic Inj. Prev. 18 (4), 431–436.

Sun, H., Frost, B.J., 1998. Computation of different optical variables of looming objects in pigeon nucleus rotundus neurons. Nat. Neurosci. 1 (4), 296–303.

Sun, M., He, D., 2025. The influence of cognitive distractions and driving experience on hazard perception performance during partially automated driving. Accid. Anal. Prev. 221, 108202.

Underwood, G., Chapman, P., Brocklehurst, N., Underwood, J., Crundall, D., 2003. Visual attention while driving: sequences of eye fixations made by experienced and novice drivers. Ergonomics 46 (6), 629–646.

Veltman, J.A., Gaillard, A., 1996. Physiological indices of workload in a simulated flight task. Biol. Psychol. 42 (3), 323–342.

Wagenmakers, E.-J., Van Der Maas, H.LJ., Grasman, R.P., 2007. An EZ-diffusion model for response time and accuracy. Psychon. Bull. Rev. 14 (1), 3–22.

Wan, J., Wu, C., 2018. The effects of lead time of take-over request and nondriving tasks on taking-over control of automated vehicles. IEEE Trans. Hum.-Mach. Syst. 48 (6), 582–591.

Wang, Y., Reimer, B., Dobres, J., Mehler, B., 2014. The sensitivity of different methodologies for characterizing drivers' gaze concentration under increased cognitive demand. Transport. Res. F: Traffic Psychol. Behav. 26, 227–237.

Wilkie, R., Mole, C., Giles, O., Merat, N., Romano, R., & Makkula, G. (2019, June). Cognitive load during automation affects gaze behaviours and transitions to manual steering control. In *Driving Assessment Conference* (Vol. 10, No. 2019). University of Iowa.

Wu, C., Wu, H., Lyu, N., Zheng, M., 2019a. Take-over performance and safety analysis under different scenarios and secondary tasks in conditionally automated driving. IEEE Access 7, 136924–136933.

Wu, L.Q., Niu, Y.Q., Yang, J., Wang, S.R., 2005. Tectal neurons signal impending collision of looming objects in the pigeon. Eur. J. Neurosci. 22 (9), 2325–2331.

Wu, Y., Kihara, K., Takeda, Y., Sato, T., Akamatsu, M., & Kitazaki, S. (2019, October). Assessing the mental states of fallback-ready drivers in automated driving by electrooculography. In 2019 IEEE Intelligent Transportation Systems Conference (ITSC) (pp. 4018-4023). IEEE.

Zeeb, K., Buchner, A., Schrauf, M., 2015. What determines the take-over time? an integrated model approach of driver take-over after automated driving. Accid. Anal. Prev. 78, 212–221.

Zeeb, K., Buchner, A., Schrauf, M., 2016. Is take-over time all that matters? the impact of visual-cognitive load on driver take-over quality after conditionally automated driving. Accid. Anal. Prev. 92, 230–239.

Zhang, B., De Winter, J., Varotto, S., Happee, R., Martens, M., 2019. Determinants of take-over time from automated driving: a meta-analysis of 129 studies. Transport. Res. F: Traffic Psychol. Behav. 64, 285–307.