TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Research Article

Transportation Research Record
1–25

DOI: 10.1177/03611981251401578
journals.sagepub.com/home/trr
Sage

Evaluating the Effects of Secondary Tasks on Driver Gaze Duration: A Duration Modeling Approach

Yasir Ali[1], Vishal C. Kummetha[2], Anshuman Sharma[3], and Alexandra Kondyli[4]

Abstract

In simulating drivers' engagement in secondary tasks in a driving simulator, the objective of this study was to investigate drivers' gaze duration when performing the tasks, reflecting the time away from the driving scene (commonly referred to as total eyes off road time [TEORT]). Eighty-five participants engaged in the secondary tasks on a driving simulator at University of Kansas, KS. TEORT values were extracted using an eye-tracker for secondary tasks, which were then modeled using a duration modeling approach. Specifically, a correlated grouped random parameters accelerated failure time Weibull duration model with heterogeneity in the mean was developed, capturing the repeated nature of observations and allowing drivers' gaze durations to be heterogeneous. The random parameter for Age Group 1 suggested that most young drivers (54%) took a shorter time to complete the secondary task, whereas the random parameter for Age Group 3 indicated that about 58% of older drivers took a shorter time to complete the secondary task. These results showed significant heterogeneity in TEORT and mixed effects on safety, whereby drivers' longer gaze duration indicated risky behavior. The findings of this study confirmed that not only was the driving behavior of one specific age group (Age Group 1) riskier than the others but that the risk within each group was not uniform—individual drivers within an age group exhibited significantly different TEORT, suggesting the need for more nuanced, intragroup analysis. The study highlights how analyzing gaze behavior can aid in designing advanced driving assistance systems to minimize distraction.

Keywords

gaze duration, distraction, duration modeling, random parameter, safety

Driving requires complete attention (or situational awareness) to the surrounding traffic dynamics, whereby drivers make longitudinal and lateral continuous decisions. Vehicle technological advancements ought to be beneficial and assist in these decisions (*1*). However, as with any scientific inventions, advancement can be a double-edged sword, which, in relation to vehicles, could lead to driving performance deteriorating (*2*).

Although driving per se is already a demanding task, engaging in a secondary task increases the workload and compromises attention on the primary driving task. A secondary task is any activity the driver performs that does not directly relate to the primary task of vehicle control and navigation. Secondary tasks divert attention from the road and can compromise safety by interfering with the driver's ability to perceive, process, and respond to traffic conditions. Secondary tasks are typically classified into three broad categories based on the type of distraction (*3*). First, visual tasks require the driver to look away from the road, such as checking a mobile phone screen, adjusting a GPS device, or reading dashboard

[1]School of Architecture, Building, and Civil Engineering, Loughborough University, Loughborough, Leicestershire, UK
[2]Center for Urban Transportation Research, University of South Florida, Tampa, Florida
[3]Department of Civil Engineering, Indian Institute of Technology (BHU), Varanasi, Uttar Pradesh, India
[4]Civil, Environmental and Architectural Engineering, University of Kansas, Lawrence, KS

Corresponding Author:
Yasir Ali, y.y.ali@lboro.ac.uk

information. Second, cognitive tasks engage the driver's mental focus, drawing attention away from driving decisions. Examples include absorbing conversations, problem-solving, or mentally rehearsing a presentation. Third, manual tasks involve physical actions that take the driver's hands off the steering wheel, such as eating, texting, or reaching for objects. Understanding and categorizing these tasks are essential for designing safer vehicle interfaces, evaluating driver workload, and developing policies to mitigate distraction-related risks.

A secondary task leads to a loss of situational awareness (or inattention), significantly increasing crash risk (*4*). The 100-Car Naturalistic Driving Study reported driver inattention as a cause of 78% of collisions, where almost 93% of rear-end collisions occurred because of drivers being distracted while driving (*5*). In the past 2 years in the United States, more than 6,600 people were killed in collisions where drivers were inattentive, engaged in secondary tasks, or both (*6*). Similarly alarming statistics can be found for the consequences of distracted driving in other parts of the world, for example, a 10% rise in fatal crashes in 2022 in the UK compared with the previous year (*7*) and a 5% to 23% increase in deaths in diverse areas of Australia (metropolitan 8%, regional 5%, and remote 28%) in 2023 compared with the previous year (*8*). Further, engaging in secondary tasks while driving may cause a delay in response to the leader's action. A study from Germany found that about 65% of drivers failed to recognize the leader or did not respond on time, which led to collisions (*9*). Therefore, understanding how a secondary task affects driving behavior and quantifying such impacts is paramount to devising tailored countermeasures and improve traffic safety.

Literature on the effects of secondary tasks spans more than two decades. Engaging in secondary tasks increases cognitive workload (*10*), which impairs driver performance. This impairment has been measured in several forms, such as deteriorated speed control, increased variation in lateral control, shorter headways, increased reaction time in responding to hazards, limited visual scanning, particularly a decline in peripheral eye scanning, and impairment in perceiving relevant stimuli (*11–13*). Driver's gazing behavior is of interest in this study because of the link between poorer driver performance and the duration a driver's eyes are diverted from the road scene to focus on a secondary task.

Gaze behavior is pivotal in understanding driver distraction as it offers a direct, quantifiable window into how drivers allocate their visual attention—a core component of safe driving (*14*). Unlike self-reports or indirect measures, gaze tracking provides real-time insights into where, when, and for how long a driver looks at specific elements inside or outside the vehicle (*15*). This aspect is crucial because when drivers engage in secondary tasks—such as adjusting a navigation system, reading a message, or interacting with in-vehicle interfaces—their gaze often shifts away from the forward roadway, increasing the likelihood of collisions (*3*). Studying gaze behavior enables the design of smarter vehicle interfaces, adaptive driver assistance systems, and distraction mitigation strategies. It also informs policy and education by identifying high-risk behaviors and guiding interventions.

Gazing behavior, often characterized by total eyes off road time (TEORT), has been studied in various ways, for example, investigating loss of comprehension (*16*), taking over after automated driving (*17*), using in-vehicle navigation systems (*18*), comparing manual versus speech-based interaction with in-vehicle information systems (*19*), using a mobile phone (*20*) (see Table 1 for further examples). However, an in-depth analysis of gazing behavior during a secondary task for different age groups and genders is relatively less explored (e.g., Cooper et al. [*21*]), despite these driver characteristics reportedly being linked to crash risk (*22*). Building on the vast literature (*23–25*), it can be hypothesized that different age groups and genders are likely to yield differential gazing behavior, and as a result, will require the use of advanced statistical (or econometric) methods beyond what has been typically used in distraction/secondary task literature (e.g., analysis of variance [ANOVA] and simple statistical analyses and models that are incapable of uncovering driver-level heterogeneity [*26*]).

Motivated by this research need, the objective of this study was to investigate drivers' gazing behavior when they are engaged in a secondary task. Specifically, the study focuses on understanding the gazing behavior of different age groups and gender using the data collected from a driving simulator experiment. The contribution of this study is twofold: firstly, it provides a deeper understanding of gazing behavior corresponding to different age groups and gender by considering driver-level heterogeneity. To this end, this study adopts a correlated grouped random parameters approach with heterogeneity in means for modeling gazing behavior. Although this modeling approach has been applied in traffic safety literature, its application for understanding the effects of secondary tasks, particularly in the context of gazing behavior, is still in its infancy. Secondly, this modeling approach reveals the gaze duration time-varying probabilities of different age groups and gender, which could be helpful in linking driving performance and the time eyes are diverted from the driving scene.

The paper is structured as follows: the next section summarizes the relevant literature and forms the background of the study; the subsequent section explains the experimental plan, including details of the driving simulator, design of the experiment, participants, secondary

Table 1. Summary of Representative Studies on Gazing Behavior

Study	Event	Participants	Technique	Heterogeneity[a]
Wikman et al. (*27*)	Cassette, mobile phone, radio	23	ANOVA	×
Bachfischer et al. (*28*)	In-car touchscreen button variation	15	ANOVA	×
Rakotonirainy et al. (*29*)	Response to avatar of another driver	12	ANOVA	×
Kim and Dey (*30*)	In-vehicle navigation display system	24	ANOVA	×
Maciej and Vollrath (*19*)	Lane change task	30	MANOVA	×
Perez et al. (*31*)	Text messaging	28	ANOVA	×
Pradhan et al. (*32*)	In-vehicle glance training	37	ANOVA	×
Heckman et al. (*33*)	Backing up using a rearview camera	77	ANOVA	×
Neurauter et al. (*34*)	Texting	44	ANOVA	×
Garrison and Williams (*20*)	Road signs and billboards	20	ANOVA	×
Hirayama et al. (*35*)	Overtaking	30	Discriminant analysis	×
Olaverri-Monreal et al. (*36*)	Engaging with heads-up display	45	ANOVA	×
Soccolich et al. (*37*)	Engaging with mobile conversations	204	ANOVA	×
Fitch et al. (*38*)	Cell phone interactions	204	ANOVA	×
Mehler et al. (*39*)	Phone calling and voice navigation	80	ANOVA	×
Zeeb et al. (*17*)	Texting and internet search	89	ANOVA	×
Carney et al. (*40*)	Cell phone usage	400	ANOVA	×
Hurtado and Chiasson (*41*)	Looking at unfamiliar road signs	50	Pairwise comparison	×
Large et al. (*42*)	Internally located digital mirrors	32	ANOVA	×
Louveton et al. (*43*)	Real-time alternative mobility choices on mobile	29	ANOVA	×
Munoz et al. (*44*)	Radio tuning and voice-based radio	156	Hidden Markov model	×
Reimer et al. (*45*)	Calls and entering address	80	ANOVA	×
Purucker et al. (*46*)	In-vehicle secondary task	18	Keystroke level modeling	×
Kaufmann and Riener (*47*)	Different types of speedometers	17	Descriptive analysis	×
Liu et al. (*48*)	Reading the message	48	Quantile regression	×
McWilliams et al. (*49*)	Cell phone interactions	72	ANOVA	×
Naujoks et al. (*50*)	Cell phone interactions	34	ANOVA	×
Biondi et al. (*51*)	Engaging with infotainment	120	ANOVA	×
Jeihani et al. (*52*)	Billboards	92	ANOVA	×
Jeong and Liu (*53*)	Stimulus–response task	24	ANOVA	×
He and Donmez (*54*)	In-vehicle secondary task	32	ANOVA, mixed effect negative binomial	✓
Miller and Boyle (*55*)	Engaging with in-vehicle information system	30	ANOVA	×
Reagan et al. (*56*)	Engaging with cell phone	80	ANOVA	×
Kohl et al. (*57*)	Album covers and contact pictures	28	ANOVA	
Cooper et al. (*21*)	Engaging with in-vehicle information system	125	Linear mixed model	×
Gomaa et al. (*58*)	Density of buildings in the scenery	79	MANOVA	×
Wang et al. (*59*)	Engaging with phone	52	ANOVA	×
Abbasi et al. (*60*)	In-vehicle gaze target while approaching roundabouts	24	Descriptive analysis	×
Kummetha et al. (*16*)	In-vehicle secondary task	90	Joint probability density functions	×
Li et al. (*61*)	Automated driving	49	ANOVA	×
Noble et al. (*62*)	Secondary tasks like phone usage and reaching out objects	18	Poisson random effect, and conditional logistic	✓

(continued)

Table 1. (continued)

Study	Event	Participants	Technique	Heterogeneity[a]
Turnbull et al. (*63*)	Secondary tasks like math problems and searching for external target objects	30	ANOVA	×
Yang et al. (*64*)	In-vehicle engagement	30	Quantile regression	×
Shabani et al. (*65*)	Traffic signs	—	Descriptive analysis	×
Monk et al. (*66*)	Mobile phone tasks	24	ANOVA	×
Xu et al. (*67*)	In-vehicle speed limit advisory system	70	Pairwise comparison	×
Yared et al. (*18*)	Navigation system displays	20	ANOVA	×
Zhang and Roberts (*68*)	Navigation task	48	Structural equation modeling	×
Zhao et al. (*69*)	Human–machine interaction	28	Correlation, principal component analysis, k-means	×
Ma et al. (*70*)	Co-pilot display	25	ANOVA	×

Note: ANOVA = analysis of variance; MANOVA = multivariate analysis of variance; — = not mentioned.
[a]Here, heterogeneity refers to unobserved heterogeneity in general and driver-level heterogeneity in gazing behavior corresponding to driver demographics.

tasks, and data preprocessing. Then, the model development process and the dataset used are described. Next, the modeling results are presented, followed by a discussion of the results. The final section summarizes the study findings and provides an outlook on future research.

Background

Abundant literature exists on driver's gazing behavior (or visual scanning/attention behavior; see e.g., Hu et al. [*71*]), and some of these representative studies are summarized in Table 1, along with a few key observations. Note that covering all studies on this topic was beyond the scope of this study, however, interested readers can refer to certain earlier studies for more detail (*3,72*).

Firstly, several studies have analyzed driver's gaze duration (characterized by TEORT) under various conditions including using mobile phones (either handheld or hands-free), engaging in secondary tasks using in-vehicle information systems (e.g., solving math problems and searching for external target objects), resuming driving from automated driving to manual driving, spending time on external stimulus such as traffic signs and billboards, and considering varied traffic conditions. This study, similar to others, is concerned with engaging in secondary tasks using in-vehicle information systems. Secondly, the analysis techniques used in past studies have mostly focused on understanding how gaze duration varies, by performing an analysis of variance (ANOVA) and simple pairwise comparisons for age groups and gender. However, these studies did not simultaneously evaluate the impact of various factors combined with driver demographics on gazing behavior, which could be attributed to using ANOVA/simple pairwise comparisons. To this end, certain studies applied statistical modeling techniques like negative binomial, conditional logistic, quantile regression, and structural equation models. Some of these applications also considered mixed effects in their models, however, driver-level heterogeneity remains unexplored (as is evident from Table 1), which again could be attributed to the lack of advanced methods employed to understand driver-level heterogeneity. This study aimed to address these gaps by applying advanced econometric models capable of uncovering driver-level heterogeneity, to assists in deciphering heterogeneous gaze behavior. These methods (e.g., random parameters with heterogeneity in means and variances) have been predominantly applied in several transport-related applications, such as response time in car-following (*73*) and lane-changing tasks (*74*), braking in response to a pedestrian crossing from a sidewalk (*75*), failed lane-changing occurrence (*76*), and an assessment of temporal instability in motorcyclists (*77*). However, application of such models for gazing behavior is relatively new, which is one of the contributions of this study.

Driving while engaged in secondary tasks (i.e., distracted) under normal conditions does not necessarily indicate increased risk. In fact, certain studies have shown that drivers can improve their performance when engaged in a secondary task, particularly in situations with low cognitive workloads (defined as "the proportion of mental capacity required by an individual to perform a task" [*78*]). For instance, Gershon et al. examined the efficacy of an interactive cognitive task (ICT) in delaying fatigue symptoms induced by underload conditions on interurban roads (*79*). The results revealed that when ICT was activated, it increased arousal, alertness, and improved driving behavior compared with when it was not activated. In another study, Atchley and Chan analyzed whether a concurrent task improved performance with decreased vigilance (*80*). Drivers were presented with three task conditions (no verbal task, a continuous verbal task, and a late verbal task): they showed improved lane-keeping performance and steering control when vigilance was at its lowest. While comparing different secondary tasks, their cognitive requirements, and their impact on driving behavior, Nijboer et al. reported that using a tablet deteriorated driving performance the most, whereas passively listening to the radio or answering questions for a radio quiz led to the best driving performance (*81*). All these findings imply that engaging in secondary tasks leads to heterogeneous driving behavior (*26*).

Although this improved driving behavior can be attributed to the low cognitive demand of the scenarios presented in previous studies, research evidence of secondary task performance in high cognitive workload environments is scant. Therefore, studying distracted driving in such environments (e.g., active work zones) presents an opportunity to address this research gap: to examine the gazing behavior (i.e., TEORT) of drivers managing secondary tasks in a high cognitive workload environment while trying to minimize any negative impact on their driving performance.

Experimental Plan and Data Collection

Driving Simulator

The study conducted a driving experiment using a fixed-base driving simulator housed in the front portion of an Acura MDX cab that runs on the miniSim platform developed by the National Advanced Driving Simulator in Iowa (*82*). The simulator features three front screens, providing a wide horizontal field of view of 170°, and a fourth rear screen that renders viewpoints of the side and rearview mirrors as shown in Figure 1.

In addition, a dash-mounted Fovio FX3 eye-tracker and 10-in. touchscreen interface were placed approximately 30° to the lower right of the driver's line of sight. An eye-tracker was utilized for recording gaze position by creating four zones of interest: driving scene, side and rearview mirror, instrument cluster, and media center or secondary task, during postprocessing. The touchscreen allowed performance of a secondary task and assisted in gauging in-vehicle distracted driving behavior (*16*, *83*, *84*).

Participants

The study received approval from the University of Kansas Human Research Protection Program. Various public locations (e.g., libraries, universities/colleges, grocery stores, and community centers) in the states of Kansas and Missouri, including the cities of Lawrence, KS, Overland Park, KS, Shawnee, MO, and Kansas City, MO, were used to advertise the study. Recruitment efforts involved distributing flyers, sending emails, and targeted advertising on Facebook. Interested individuals had to complete a prescreening questionnaire that gathered information on demographics, driving experience, crash history, medical conditions, and so on. To be eligible for participation and monetary compensation on successful completion of the experiment, individuals had to meet the following criteria: to be between 18 and 65 years old, hold a valid U.S. driver's license, have at least 1 year of driving experience, cover an annual driving distance of more than 1,600 km (1,000 mi), and be in a satisfactory medical condition, meaning they were free from heart conditions, noncorrectable eye conditions, seizures, inner-ear/balance problems, and the possibility of pregnancy.

From the registered participants, 85 eligible individuals performed the experiment. The mean and standard deviation of age of the participants were 31.4 and 14.2 years, respectively. Males and females were almost equally represented in the sample. The average annual mileage for all participants was 19,400 km, with a standard deviation of 13,780 km (*85*).

Scenario and Testing Protocol

On arrival at the laboratory, participants were provided with an explanation of the informed consent process and given a brief tutorial on how to operate the driving simulator. Following this, they performed a 10-min warm-up scenario comprising rural highway driving (speed limit of 112.7 km/h [70 mph]) with a very low traffic density (0 to 2 passenger cars per kilometer per lane (pc/km/ln) equivalent to Level of Service A) to familiarize themselves with the virtual environment, simulator, and process of the experiment. Once the warm-up drive was completed, participants started the actual driving experiments and engaged in a distracted driving task. This task involved driving along an 8-km stretch of a 10- to 12-lane divided freeway, with a posted speed limit of 112.7 km/h (70 mph), traffic density varying between 22 and 24 pc/km/ln (Level of Service of D/E), and active work zones on both sides of the road, leaving two open lanes (as depicted in Figure 2). No pedestrians were present on the roadway at any point of the drive.

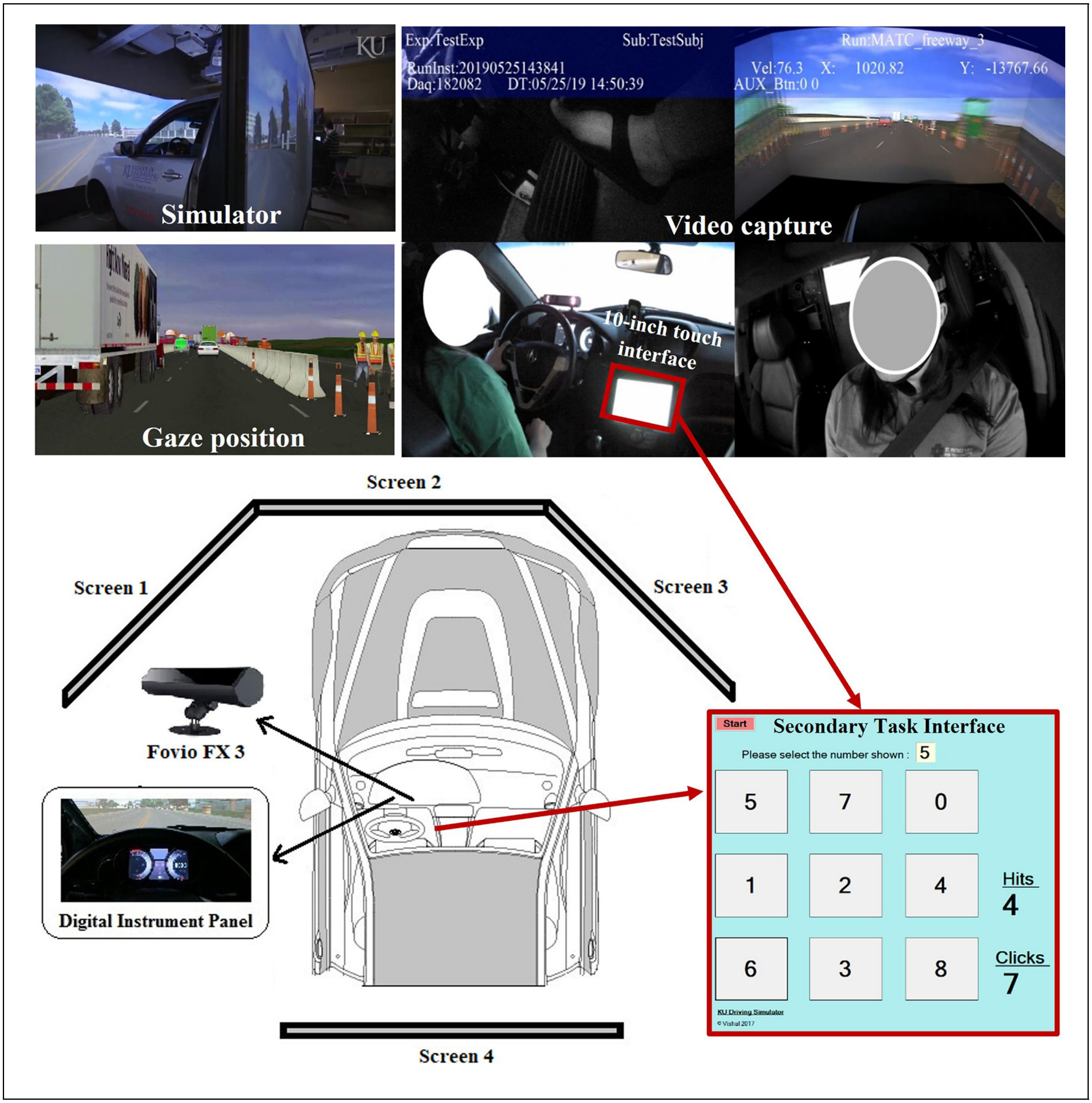


Figure 1. Equipment setup and configuration.

During the tutorial phase, participants were also screened for simulator sickness. Any participants who showed severe signs of simulator sickness (e.g., vertigo, nausea, sweating, dizziness, fatigue, stomach awareness, vomiting, and general discomfort) were advised to withdraw from the study. The experimental layout was also kept short and comprised minimal turning movements to minimize any potential discomfort and reduce the likelihood of simulator sickness. Of the 90 scheduled participants, five withdrew from the study because of symptoms of simulator sickness.

Data from the first and last 0.8 km (0.5 mi) were excluded from the analysis to provide sufficient time for participants to reach the posted speed limit and to exclude any deceleration trends observed toward the end of the drive (*85*, *86*). Participants were additionally required to fill out the National Aeronautics and Space Administration Task Load Index (NASA-TLX) and

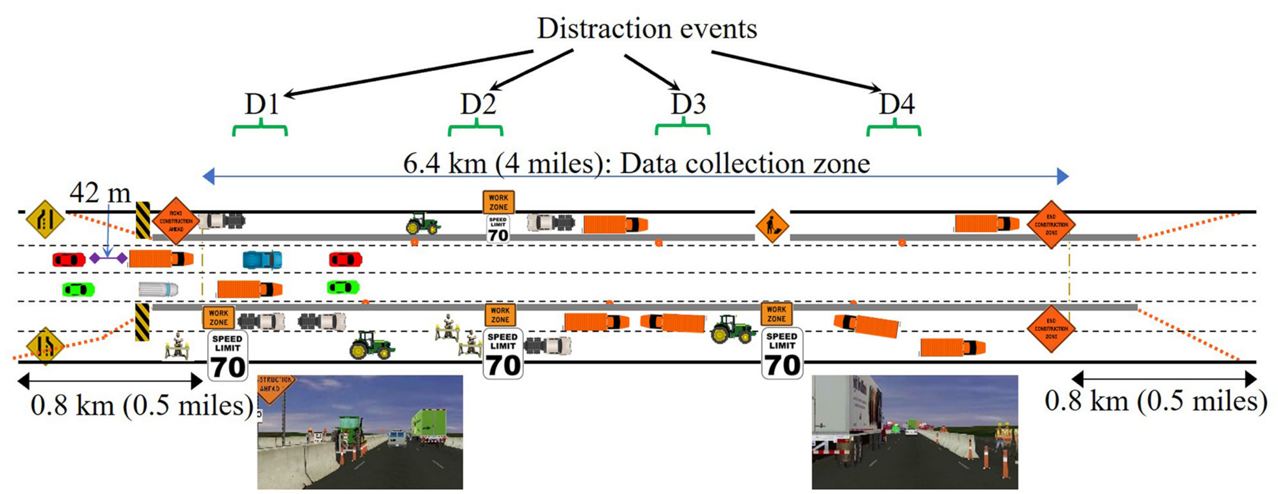


Figure 2. A general schematic of task layout and road geometry.

Situational Awareness Rating Technique (SART) questionnaires on completing the tutorial (i.e., baseline) and after the distracted driving task, offering a subjective assessment of their experience. The NASA-TLX is a validated measure of cognitive workload, consisting of six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration (*87*). Each subscale is scored on a 20-point scale and weighted based on 15 pairwise combinations. A higher NASA-TLX score, compared with the baseline condition, indicates increased cognitive workload. To assess changes in situational awareness, the SART questionnaire was administered in a similar manner to the NASA-TLX. Situational awareness scores were calculated by averaging the 10 individual subscales across three domains: attentional demand, attentional supply, and understanding (*88*). (The overall comparison of cognitive perceptions of the distraction task to the baseline, across the participants, is available in Appendix A in Supplemental Material.)

Secondary Task

As mentioned in the background section, to date, less emphasis has been placed on studying distracted driving behavior in high cognitive workload environments. This study addresses this gap by utilizing work zones to simulate high cognitive workloads to enforce the detrimental repercussions (i.e., loss of lateral control and increased crash risk) of distracted driving. This setting results in more naturalistic risk perceptions and tailored gazing behaviour during the simulated task, thus overcoming low cognitive workload environments (i.e., empty rural highways, ideal weather conditions, very low traffic densities, and conditions with low probability of change to the required cognitive resources) that are often overlooked by drivers.

The distracted driving task included four separate distraction events, each lasting no longer than 25 s (referred to as D1 to D4 in Figure 2). These events were triggered using audio commands (i.e., start/stop, using the GPS) and were designed to simulate scenarios such as using the media center or entering text into an onboard navigation system (as illustrated in Figure 1). The four distraction events required participants to perform a visual secondary task while driving by matching a number displayed in a box on the top-right of the panel ("Please select the number shown," as shown in Figure 1) with the corresponding number on one of the nine randomly varying tiles. The application also recorded and displayed the number of correct matches (hits) and total attempts made (clicks), aiming to keep participants visually and cognitively engaged throughout the task.

Preprocessing

Eighty-five participants successfully completed the distraction task, and four distracted driving observations were obtained per participant, as shown in Figure 2, producing a panel dataset of 340 observations for 85 participants. Four distraction events were included during the drive to provide repeated observations at different points (i.e., early, midway, and later) in the scenario. This approach minimized the possibility that the findings were the result of a one-off instance or order bias, instead highlighting consistent behavioral adjustments.

As this research focused on utilizing changes in driving performance (i.e., fluctuations observed in lateral

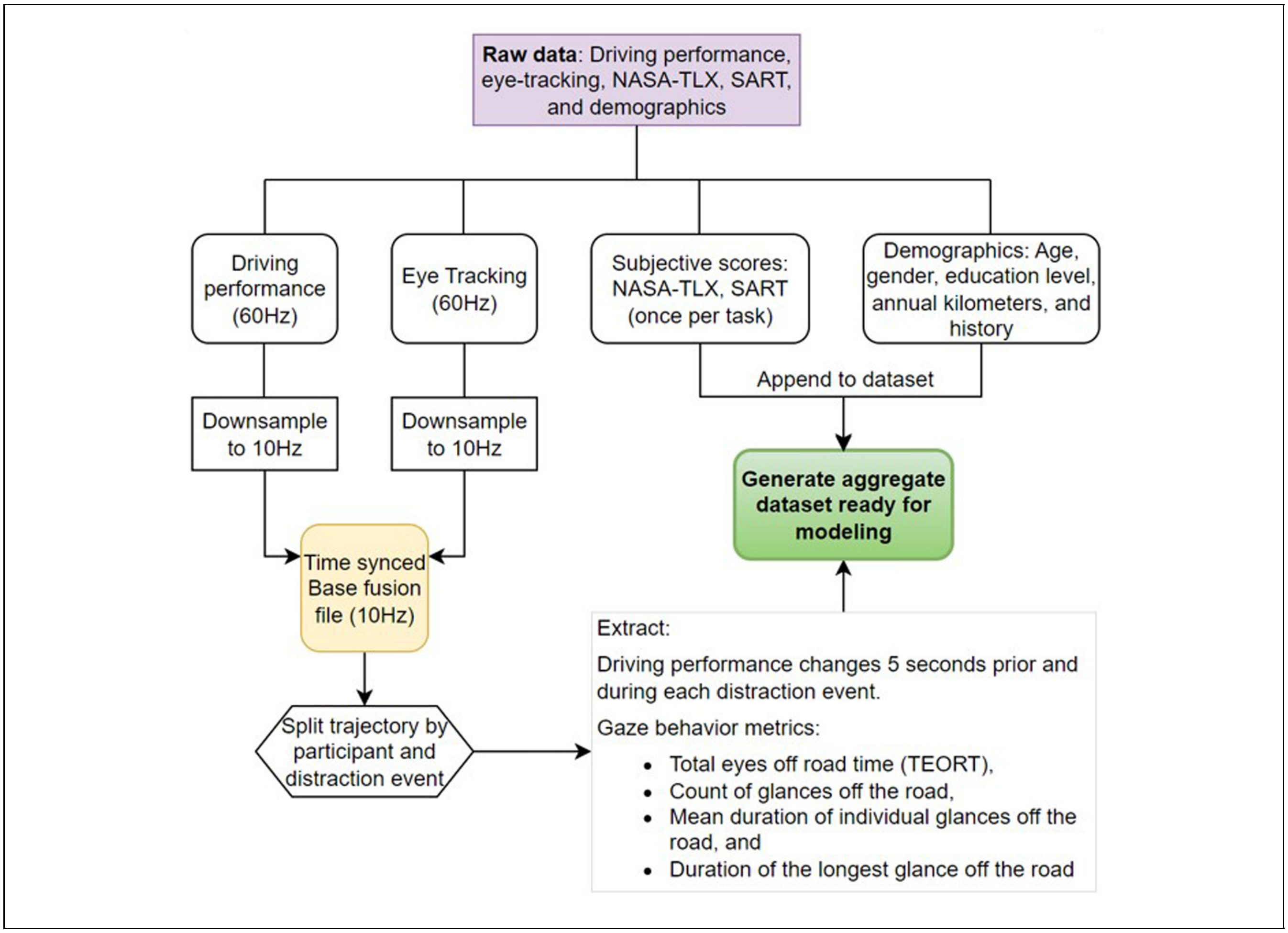


Figure 3. Data extraction framework.

and longitudinal driving) and the time spent gazing away from the driving scene (defined as the sum of the gaze durations directed toward attempting the distraction task in a given scenario, or TEORT) during the duration event, data fusion was employed to merge the raw driving performance and eye-tracking datasets, as shown in Figure 3. The raw data were downsampled from 60 to 10 Hz for processing efficiency and then fused based on system time. Individual trajectories were then split with respect to the distraction events (shown in Figure 4), allowing for the extraction of driving performance and gazing behavior within the period of interest.

Hazard-Based Duration Model Development

As discussed in the previous section, the purpose of this study was to understand drivers' gazing behavior, measured as the time (or duration) spent on attempting the distraction task (or TEORT). In other words, the duration variable represents the collective time spent on four distractions per participant. To model duration data, this study applied a hazard-based, or survival, duration modeling approach. This probabilistic approach is deemed fit for modeling duration data where a need arises to model the elapsed time until the end of an event or the duration of an event. Duration models have been frequently used for various transport applications, such as studying the time until a crash occurs, the time to respond to pedestrians walking from the sidewalk, and the length of time spent shopping and engaging in recreational activities (*89*).

In general, duration models are employed to model the conditional probability of the duration of an event ending at time t, given that the event duration has not ended until time t. Using the same definition, this study models drivers' total gaze durations when they perform secondary tasks and take their eyes away from the driving scene. In other words, the duration variable represents the time taken to complete the secondary task,

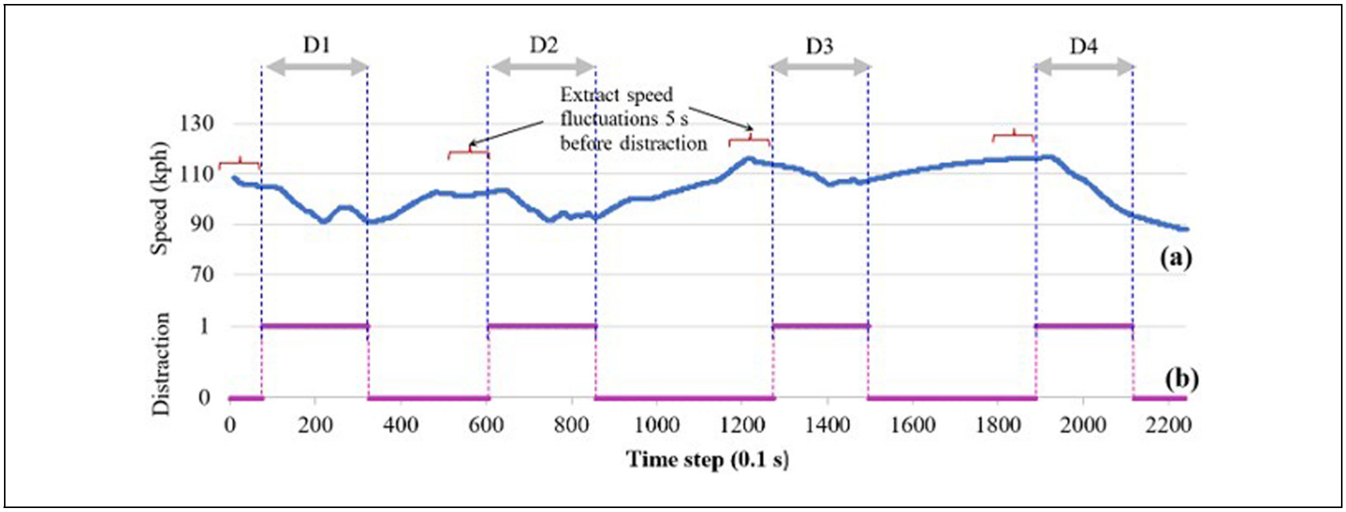


Figure 4. A typical time-series profile of (*a*) speed and (*b*) distraction.
Note: Data from Driver 3.

which is characterized by TEORT. Note that while calculating this time, it was ensured that the driver was engaged in and looking at the task. TEORT is a continuous random variable, T, with a cumulative function, $F(t)$, and probability density function, $f(t)$. Note that $F(t)$ is also known as a failure function in the literature (*90*); in the context of this study, it gives the probability of a driver starting to perform the secondary task in response to the verbal command before some specified time, t. Mathematically, it is obtained by

$$F(t) = Pr(T < t) = 1 - Pr(T \geqslant t) = 1 - S(t). \quad (1)$$

Similarly, the survival function, $S(t)$, yields the probability that the drivers' gaze will revert to the driving scene in a time greater than a specified time, t. Another term frequently used in duration modeling is hazard function, $h(t)$, which provides the rate at which the event duration ends at time t, given that the event duration has survived up to time t. Since the event has not ended by time t, the hazard function provides the conditional probability that an event will end between time t and $t + dt$. Mathematically, the hazard function can be defined as

$$h(t) = \frac{f(t)}{1 - F(t)} = \frac{f(t)}{S(t)} = \lim_{\Delta t \to 0} \frac{Pr(t + \Delta t \geqslant T \geqslant t | T \geqslant t)}{\Delta t} \quad (2)$$

Proportional hazard and accelerated failure time (AFT) approaches are used to incorporate the effects of covariates on a hazard function. Whereas the former approach assumes that the hazard ratios are constant over time, whereby the covariates act multiplicatively on the baseline hazard function, $h_0(t)$, the latter approach makes it relatively simple to incorporate the effect of covariates by rescaling time directly in a baseline survival function, $S_0(t)$, where all covariates are zero (*89*). AFT estimates an acceleration factor that captures the direct effect of exposure on survival time, facilitating an intuitive and more straightforward interpretation of the model. Given the estimated parameters of an AFT model quantify the corresponding effect of a covariate on gaze durations, this modeling approach was adopted in this study.

Mathematically, the natural logarithm of TEORT, $\ln(t_{iq})$, is expressed as a linear function of covariates in the AFT model as

$$\ln(t_{iq}) = \alpha + \boldsymbol{\beta} \boldsymbol{X_{iq}} + \sigma \varepsilon_{iq} \quad (3)$$

where t_{iq} is TEORT for each driver $i \in (1, \ldots, 85)$ in secondary task $q \in (1, 2, 3, 4)$; α is constant (to be estimated); $\boldsymbol{\beta_i}$ denotes vector of unknown (to be estimated) driver-specific parameters; $\boldsymbol{X_{iq}}$ indicates that vector of covariates (see Table 2) and ε_{iq} are independently and identically standard Gumbel-distributed random errors; and σ is scale parameter (to be estimated). The conditional survival and hazard functions for the accelerated failure model can be obtained by

$$S(t|\boldsymbol{X}) = S_0[t \times \mathrm{EXP}(\boldsymbol{\beta X})], \quad (4)$$

$$h(t|\boldsymbol{X}) = h_0[t \times \mathrm{EXP}(\boldsymbol{\beta X})] \times \mathrm{EXP}(\boldsymbol{\beta X}), \quad (5)$$

where S_0 and h_0 are baseline survival function and hazard function, respectively.

From Equations 4 and 5, a direct relationship between the effects of covariates and TEORT can be observed, implying that these covariates may increase or decrease TEORT.

Table 2. Descriptive Summary of Explanatory Variables Considered for the Duration Model

Categorical (or count) variables	Role of the variable in analysis	Analysis	Description of variables	Count (%)
Age groups				
Young	Independent	MANOVA and duration model	Participant is 18−24 years old (dummy)	44 (51.76)
Middle-aged	Independent	MANOVA and duration model	Participant is 25–49 years old (reference)	27 (31.76)
Older	Independent	MANOVA and duration model	Participant is 50+ years old (dummy)	14 (16.48)
Gender				
Male	Independent	MANOVA and duration model	Participant is male (reference)	43 (50.59)
Female	Independent	MANOVA and duration model	Participant is female (dummy)	42 (49.41)
Count of glances	Dependent	MANOVA	Number of discrete times a driver's gaze is directed off the road within the distraction tasks	41.42 (16.350)
Continuous variables	**Role of the variable in analysis**	**Analysis**	**Description of variables**	**Mean (SD)**
Initial speed	Independent	Duration model	Instantaneous speed of the subject vehicle at the onset of the secondary task (m/s)	24.22 (10.11)
Speed fluctuations	Independent	Duration model	The variation in speed 5 s before the secondary task (m/s)	0.868 (0.391)
Vehicle kilometers driven	Independent	Duration model	Number of vehicle kilometers driven from actual driving experience in 1000	12.15 (8.54)
TEORT	Dependent	MANOVA and duration model	Total eyes off road time (s)	6.16 (4.35)
Mean duration of individual glance	Dependent	MANOVA	Mean duration in seconds of the individual glances off the road during the distraction tasks (s)	0.85 (1.92)
Duration of longest glance	Dependent	MANOVA	Maximum duration in seconds of the longest individual glance off the road during the distraction tasks (s)	3.40 (4.02)

Note: TEORT = total eyes off road time; MANOVA = multivariate analysis of variance; SD = standard deviation.

For specifying a parametric distribution of the duration variable, various distributions are used in the literature, including Weibull, lognormal, exponential, gamma, log-logistic, and Gompertz (*89*). Selecting a particular distribution is often based on theoretical justification or statistical testing, as it has direct implications on the underlying hazard function and potential bias of the estimated parameters. Theoretically, a Weibull distribution is suitable for data with monotonic hazard rates that either exponentially increase or decrease with time. Drivers' TEORT when engaged in secondary tasks represents a positive duration dependence event, where drivers reverting their gaze to the driving scene increases monotonically, and the probability of gaze reverting to the driving scene is likely to increase over time. The Weibull duration model is particularly suitable for positive duration dependence events, which was relevant to this study. Further, the fitted distribution of TEORT was statistically tested using an Anderson–Darling test, and its result confirmed that our data followed a Weibull distribution ($p > 0.05$). Beyond these two reasons, this study estimated models with other distributions like lognormal and logistic, and compared them using goodness-of-fit measures (likelihood values) and Cox–Snell residuals, and the model with the Weibull distribution outperformed all competing models. Based on the theoretical and statistical evaluation, this study adopted the Weibull distribution (see Washington et al. [*89*] for details of the hazard and survival functions).

In practice, different drivers may revert their gaze to the driving scene at different times depending on their personal characteristics and risk-taking behavior. Therefore, an interaction term (e.g., age or gender) might be used in the model, which might explain this behavior to some degree; however, two issues persist. Firstly, finding and testing all possible combinations of interaction terms is challenging because the number of potential combinations of variables and their higher-order interactions grows geometrically with the number of ordinal-scale variables and exponentially with nominal-scale variables. Secondly, even using all possible interaction terms in a fixed parameters model would provide only an average effect for a given interaction term (e.g., Age Group 1 with females), because a fixed parameter model assumes that all drivers spend the same time performing the secondary tasks. To capture individual or driver-level heterogeneity, a random parameters approach has been proposed in the literature (*73*, *91*), and was adopted in this study as, by allowing the estimated parameters to vary across individual drivers, it captures the preference heterogeneity and differential effects of the same treatment on different individuals. Specifically, by using random parameters in the hazard-based duration model, we consider $\boldsymbol{\beta}_\mathbf{i}$ to be driver-specific random parameters for the operational variables defined as

$$\boldsymbol{\beta}_\mathbf{i} = \boldsymbol{\beta} + \Gamma\gamma_i, \tag{6}$$

where

$\boldsymbol{\beta}$ is vector of mean values of the random parameter,

γ is user-specified term (e.g., gamma distributed, a normally distributed term), and

Γ represents the Cholesky matrix.

This study used an unrestrictive form of the Cholesky matrix (*92*) that allows capturing correlations between two or more random parameters, as well as accounting for the panel nature of data. In the literature, this modeling framework is often called "correlated grouped random parameters with heterogeneity in the mean" (*93*). Behaviorally, incorporating correlated random parameters assists in capturing the correlation among unobserved heterogeneities (or characteristics) that are encapsulated by random parameters. For example, the unobserved factors that influence the effect of age on TEORT might be correlated with unobserved factors that influence the effect of gender on TEORT.

This study employed a maximum simulated likelihood estimation technique for the random parameters model for two reasons. Firstly, in random parameters models, some coefficients (e.g., for Age Group 1, Age Group 3) are assumed to vary across individuals or observations, typically following a specified distribution (i.e., normal), which introduces integration over the distribution of random parameters into the likelihood function, and this integral becomes analytically intractable. As such, using the maximum simulated likelihood estimation procedure becomes feasible, allowing us to account for unobserved individual-level variation in a statistically rigorous way, even when the likelihood function cannot be expressed in closed form. Secondly, because our dataset contains repeated observations of the same participant, using the same draw of $\boldsymbol{\beta}_\mathbf{i}$ for each participant from the specified distribution becomes easier. To obtain parameter estimates, a maximum likelihood approach using quasi-Monte Carlo simulation was adopted, whereby 1,000 Halton draws were used to account for the panel nature of the data (*94*).

To interpret the model parameters and their effects on gaze duration, the exponent of each coefficient, exp (β) - 1) $\times$ 100, was computed, reflecting a per cent change in TEORT corresponding to a unit increase in the continuous variable or a change from 0 to 1 for categorical variables.

In most driving simulator studies, duration models are applied to study relative changes in driving behavior, whereby the results are compared with a baseline condition (e.g., comparing car-following behavior with and without driving aids [*73*]). However, in this study, we intentionally did not use the baseline (tutorial) for modeling purposes because drivers' gaze during the baseline condition (without a secondary task) was almost always on the driving scene, thereby resulting in a value of zero for time spent gazing at the secondary task.

Results

Preliminary Analysis

To fully understand gaze behavior during the secondary task across age groups and gender, this study performed a preliminary analysis using a repeated measures multivariate ANOVA (MANOVA) and duration modeling sequentially. This study evaluated four independent variables by aggregating the four distraction events, that is, TEORT, count of glances off the road, mean duration of individual glances off the road, and duration of the longest glance off the road (*27*, *54*). Figure 5 shows the box plots of these metrics, categorized by gender and age group (independent variables). Overall, the TEORT, count of glances, and mean duration of glances showed slight differences between the groups, warranting further investigation.

A repeated measures MANOVA was performed as a first-level check to statistically examine whether differences existed across gender, age group, and their interaction with the distraction-related measures before applying the more complex, correlated random

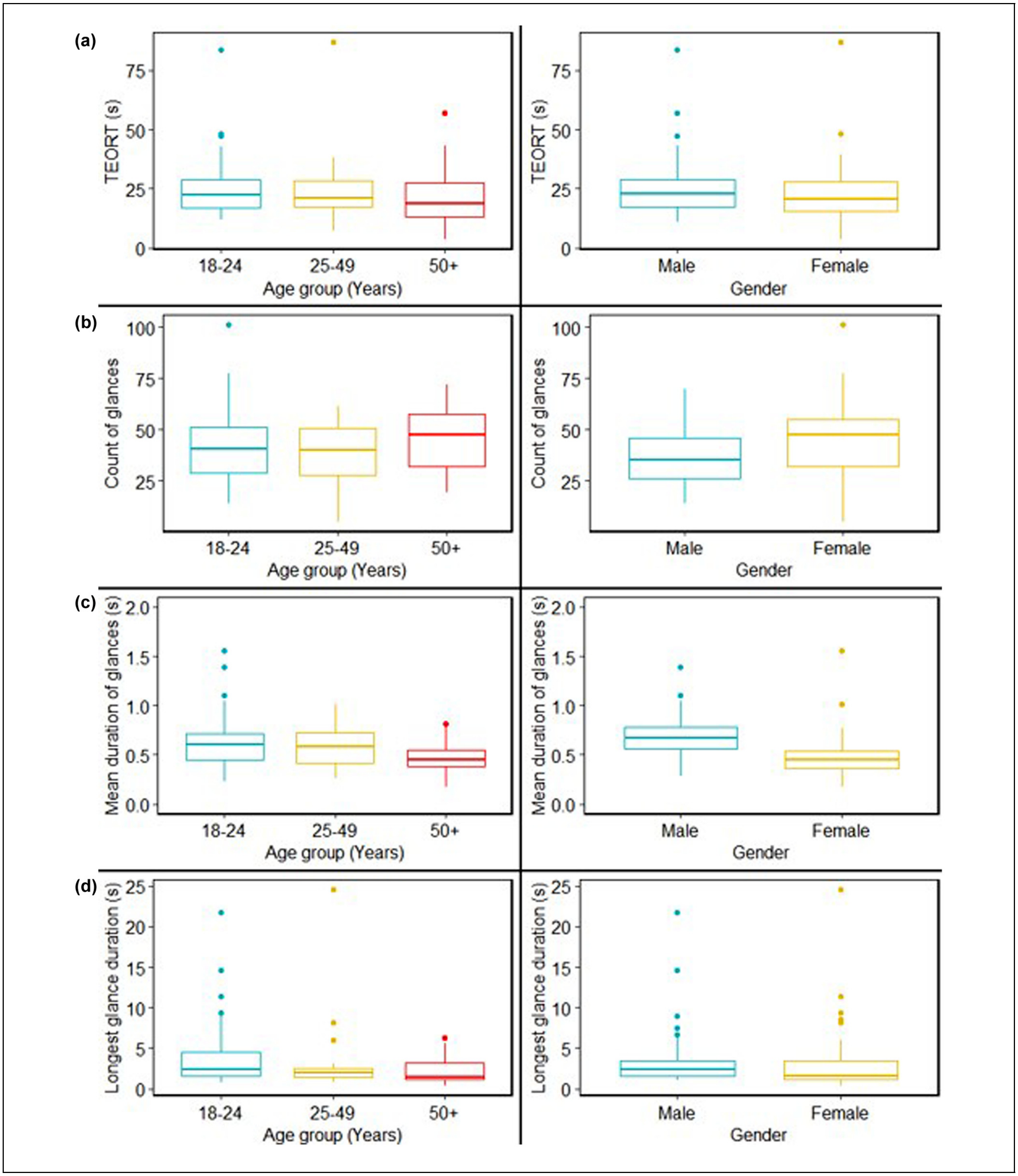


Figure 5. Box plots of gaze behavior metrics by age group and gender: (*a*) TEORT, (*b*) count of glances, (*c*) mean duration of glances, and (*d*) longest glance duration.

Note: TEORT = total eyes off road time.

Table 3. MANOVA Summary Statistics

Dependent variable	df	M^2	F-statistic	Significance	Partial eta^2	Observed power
Intercept						
TEORT	1	39846.722	217.062	<0.001	0.733	1.000
Count of glances	1	120621.850	480.854	<0.001	0.859	1.000
Mean duration of individual glance	1	43.321	11.740	<0.001	0.129	.923
Duration of longest glance	1	665.386	41.485	<0.001	0.344	1.000
Age group						
TEORT	2	31.105	0.169	0.844	0.004	0.075
Count of glances	2	165.646	0.660	0.520	0.016	0.157
Mean duration of individual glance	2	2.536	0.687	0.506	0.017	0.162
Duration of longest glance	2	13.114	0.818	0.445	0.020	0.185
Gender						
TEORT	1	186.160	1.014	0.317	0.013	0.169
Count of glances	1	826.482	3.295	0.073	0.040	0.434
Mean duration of individual glance	1	0.350	0.095	0.759	0.001	0.061
Duration of longest glance	1	1.942	0.121	0.729	0.002	0.064
Age group × gender						
TEORT	2	248.127	1.352	0.265	0.033	0.283
Count of glances	2	393.178	1.567	0.215	0.038	0.323
Mean duration of individual glance	2	5.506	1.492	0.231	0.036	0.309
Duration of longest glance	2	26.978	1.682	0.193	0.041	0.344
Error						
TEORT	79	183.573				
Count of glances	79	250.849				
Mean duration of individual glance	79	3.690				
Duration of longest glance	79	16.039				

Note: TEORT = total eyes off road time; MANOVA = multivariate analysis of variance.
Actual group means are presented in Appendix Table B1 (Supplemental Material) to provide the descriptive statistics for each age and gender group, complementing the overall MANOVA results presented in Table 3.

parameters duration model. Unlike a standard ANOVA, which examines each dependent variable separately, the repeated measures MANOVA tests all four dependent variables simultaneously, accounting for correlations among them and providing a multivariate test of group and interaction effects. Further, although there were three age groups in the study, Table 3 does not show descriptive statistics by age/gender group; instead, it presents the MANOVA summary statistics (degrees of freedom, mean squared, *F*-statistic, significance, and effect size) for the age group (or gender) factor as a whole, and only one set of summary statistics per dependent variable is shown (e.g., "Age Group"). From the descriptives shown in Table B1 of the Appendix, differences in means were observed across the dependent variables and the groups. However, high standard deviations were also noted, reflecting a wide range of variation among participants' responses to the secondary task.

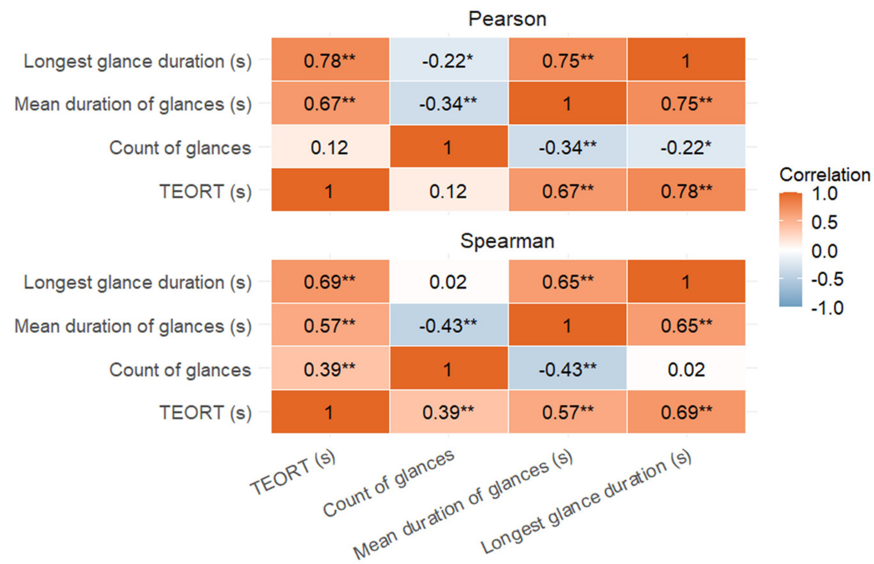
No significant results were obtained at a 95% confidence level, indicating no between-group differences in observations of the dependent variables. However, more complex statistical methods like hazard-based duration models considering random effects and group heterogeneity are likely to provide valuable insights into the effects of these variables on TEORT.

As an initial step, correlation tests (Figure 6) were conducted to identify variables suitable for duration modeling. The Spearman and Pearson tests revealed significant correlations among the four variables of gaze behavior. Each of these metrics (except for glance count) was tested for duration modeling (as a response variable), but only TEORT showed significant relationships, allowing us to investigate gazing behavior for different age groups and gender (the study objective).

Modeling Results

Several variants of the random parameters duration models were estimated to understand gazing behavior. These models included a fixed parameters model, and random parameters models with and without heterogeneity in the mean, and correlation between the random parameters. These models were compared with each other, and the best model was selected based on a series of likelihood ratio tests and the Akaike information criterion (AIC).

Comparing the fixed- and random parameters models, the likelihood ratio statistic, $\chi^2 = -2[-291.13 - (-277.41)] = 27.44$, with four degrees of freedom, indicated that the null hypothesis that both models



**Correlation is significant at 5% level, ***Correlation is significant at 1% level.*

Figure 6. Correlation assessment of gaze metrics.

were the same could be rejected with 90% confidence. Similarly, comparing the uncorrelated and correlated random parameters, the test statistic, $\chi^2 = -2[-283.78 - (-277.41)] = 12.74$, with one degree of freedom, indicated that the null hypothesis that both models were the same could be rejected with 90% confidence. Finally, the test statistic for comparing the correlated random parameters model with heterogeneity in the mean versus without heterogeneity in the mean, $\chi^2 = -2[-281.22 - (-277.41)] = 7.62$, with three degrees of freedom, indicated that the null hypothesis that both models were the same can be rejected with 90% confidence. The AIC for the fixed parameters and correlated random parameters models were 596.26 and 576.82, respectively, suggesting the latter model outperformed its counterpart. Further, the AIC for the correlated versus uncorrelated random parameters models were 576.82 and 587.56, respectively, implying that the correlated model was superior to the uncorrelated model. Finally, the AIC for the correlated random parameters models with and without heterogeneity in the mean were 576.82 and 582.44, respectively. This comparison indicated that the correlated random parameters model with heterogeneity in the mean outperformed all competing models and was therefore selected in this study.

Although Table 4 presents the parsimonious model with main effects, several interaction effects were tested in the model, namely age and gender, and only one interaction effect (i.e., heterogeneity in the mean: female $\times$ Age Group 3) was found to be significant. All other interaction effects were tested in the model but were not retained because they neither showed statistical significance nor improved overall model goodness-of-fit. Further, to handle potential confounding variables, the models were developed separately for each (e.g., age and driving experience). The parsimonious model was selected based on the intuitive relationship of the variable, statistical significance, and overall model goodness-of-fit.

Table 4 presents the model estimation results for the correlated random parameters duration model with heterogeneity in the mean. All parameter estimates were statistically significant at a 90% confidence level. The model's scale (or Weibull) parameter (P) was 2.279, and a t-test on this parameter suggested that it was significantly greater than 1.0 ($t = 14.27$, $p < 0.001$), indicating an increasing hazard function, implying that the secondary task event completion probability increased with elapsed time. Further, the model comprised both random and nonrandom parameters, whereby the dummy variables for Age Group 1 and Age Group 3 represented the former group. Several distributions were explored for random parameters (e.g., normal, lognormal, Weibull, uniform, and triangular). The normal distribution provided a statistically superior model fit relative to other distributions tested in this study, which was consistent with past literature (*95*). In addition, the normal distribution captured the negative and positive effects of age groups on TEORT, implying that gaze duration might increase or decrease for young drivers (considering Age

Table 4. Estimation Results of the Random Parameters Duration Model

Parameter	Estimate	SE	*z*-statistics	*p*-value	exp(β)	CI of exp(β) Upper	CI of exp(β) Lower
Nonrandom parameters							
Constant	0.3919	0.0772	5.07	<0.001	na	na	na
Initial speed (at onset of task)	0.0044	0.0025	1.77	0.0760	1.0044	0.9995	1.0093
Speed fluctuation	−0.1839	0.0507	−3.63	0.0003	0.8320	0.7326	0.9314
Number of kilometers driven	−0.0045	0.0013	−3.47	0.0005	0.9955	0.9930	0.9981
Random parameters							
Age Group 1 (18−24 years)	−0.0337	0.0202	1.67	0.0958	0.9669	0.9273	1.0065
Age Group 3 (50+ years)	0.0573	0.0342	1.68	0.0937	1.0590	0.9919	1.1260
Diagonal elements of the Cholesky matrix							
Age Group 1 (18−24 years)	0.1623	0.0159	10.19	<0.001	1.1762	1.1450	1.2074
Age Group 3 (50+ years)	0.1214	0.0254	4.48	<0.001	1.1291	1.0793	1.1789
Below diagonal element of the Cholesky matrix							
Age Group 1:Age Group 3	−0.0867	0.025	−3.61	0.0030	0.9170	0.8680	0.9660
Heterogeneity in the mean of Age Group 3							
Female	−0.2173	0.0538	−4.04	0.0010	0.8047	0.6992	0.9101

Note: SE = standard error; CI = confidence interval; na = not applicable.
LL (β) = −277.41, LL (0) = −307.33, AIC = 576.82, N = 340, scale parameter = 2.279 ($p < 0.001$); number of groups = 85; group size = 4.

Group 1). The remaining parameters were nonrandom and consisted of the number of kilometers driven, speed fluctuations, and initial speed (at the onset of the secondary task). Note that several demographic variables (e.g., crash history in the past 5 years, traffic violation history in the past 2 years, cell phone use while driving, and education level) were tested in the model, but these variables were not retained in the parsimonious model as a result of statistical insignificance.

Table 4 also provides the diagonal and below diagonal elements of the Cholesky matrix for each random parameter. Using these elements, the standard deviation of each random parameter can be calculated as the square root of the variance (i.e., elements of the variance-covariance matrix obtained via $\Omega\Omega'$). For example, the standard deviations for the Age Groups 1 and 3 parameters are computed as $\sqrt{0.0263} = 0.1623$ and $\sqrt{0.0222} = 0.1491$, respectively.

Initial speed—measured at the onset of the secondary task—had a significant and positive relationship with TEORT in the model. By keeping other variables constant, a 1 m/s increase in the initial speed tended to increase gaze durations by 0.4%. Similarly, speed fluctuation—measured as the standard deviation of speed 5 s before the secondary task—was negatively associated with TEORT in the model, with an increase of 1 m/s in speed fluctuations tending to decrease gaze duration by 16.8%. Further, the number of kilometers driven was significant and negatively associated with TEORT. The model suggested that gaze duration decreased with a greater number of kilometers driven: every 1,000 km decreased gaze duration by 0.45%.

Both the mean and standard deviation of the normally distributed parameter of the Age Group 1 dummy variable were statistically significant ($p < 0.001$). The mean value suggests that relative to Age Group 2, on average, Age Group 1 took about 3.31% less time reverting their gaze to the driving scene. We also observed significant heterogeneity in TEORT for drivers within Age Group 1, showcasing an ability to be both longer and shorter in duration compared with Age Group 2. Age Group 1's distribution is depicted in Figure 7*a*, indicating that about 52% of its generated coefficients were actually negative, whereas the remainder were positive, confirming heterogeneity. Further, driver gender was found to influence the TEORT of Age Group 1. Therefore, we decomposed the distribution of Figure 7*a* to obtain two separate distributions as per Figure 7*c*. As such, we obtained a mean survival rate of 0.807 and 1.03 s for females and males, respectively, indicating the relatively shorter gaze durations of female drivers. We discuss this gender effect further in the next section.

The mean parameter for the Age Group 3 dummy variable was significant and positively associated with TEORT. The model revealed that drivers in Age Group 3 took more time to complete the secondary task compared with Age Group 2: this could be associated with several factors like cautious driving, task difficulty, or slower sensory motor and processing power—more details to follow in the next section. Similar to Age Group 1, heterogeneity was observed, whereby the majority of drivers obtained a negative coefficient, whereas 42% maintained a positive value, see Figure 7*b*, suggesting significant driver heterogeneity in this context.

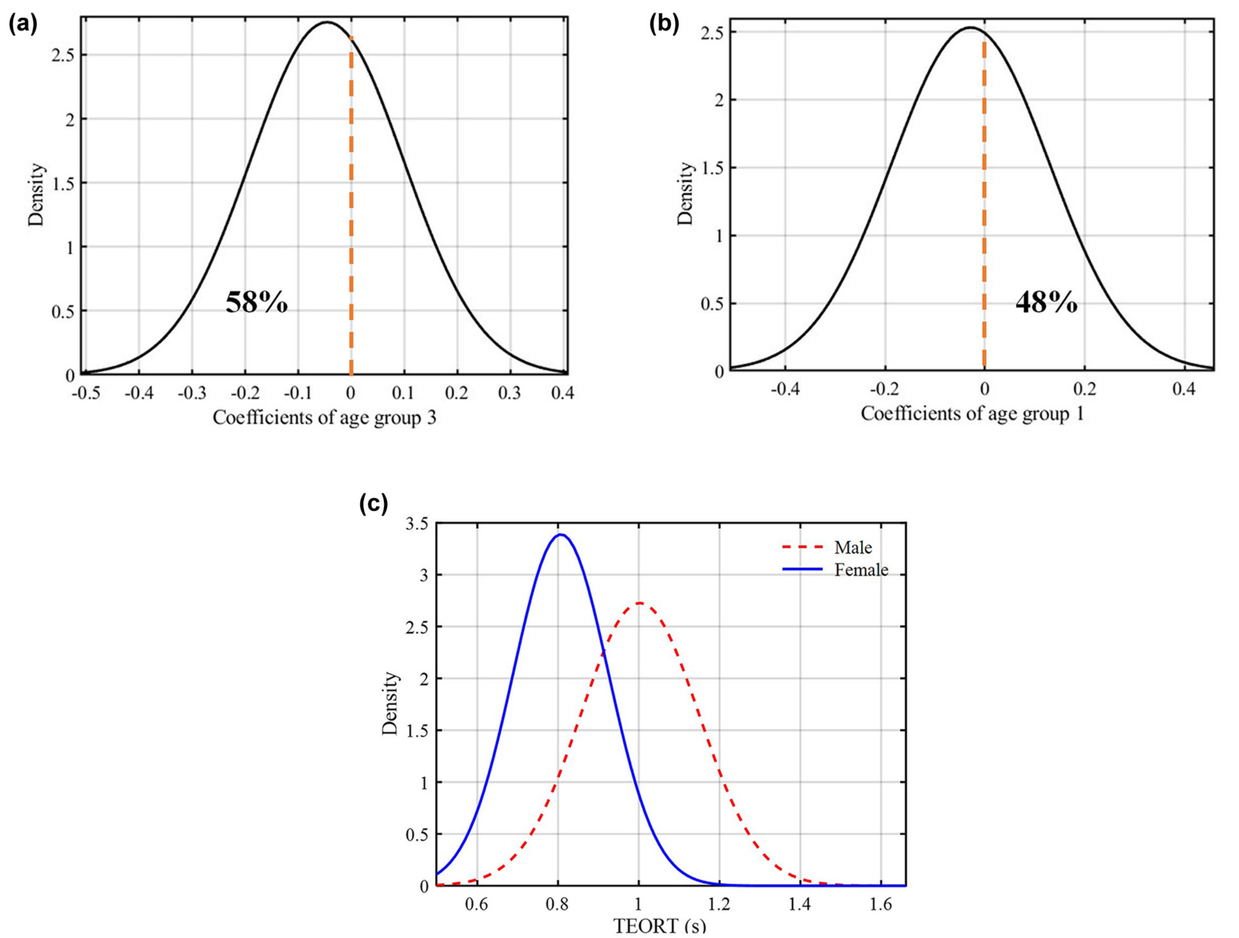


Figure 7. Distributional effect of the random parameters: (*a*) Age Group 1, (*b*) Age Group 3, and (*c*) TEORT for male drivers versus female drivers.
Note: TEORT = total eyes off road time.

Because of the unrestricted form of the Cholesky matrix, we were able to investigate the correlation between the random parameters, offering more insights into the gaze behavior of drivers during the secondary tasks. The results indicated that the random parameters for Age Groups 1 and 3 correlated at a 90% confidence level (t-statistic = 5.66; $p < 0.001$), with a covariance of -0.014 and a correlation coefficient of -0.58. The t-statistic and correlation coefficients were calculated following the postestimation technique presented in Fountas et al. (interested readers are referred to their study for details [*93*]). The correlation between random parameters uncovered the unobserved heterogeneity associated with the interactive effect of random parameters on gazing behavior (*96*). A negative correlation between the random parameters (i.e., Age Group 1 and Age Group 3) implied mixed effects of age on the gazing behavior of drivers. Specifically, relative to Age Group 2, drivers in Age Groups 1 and 3 might either take a shorter or longer time to complete their secondary tasks. This heterogeneous behavior might be explained by age: with increasing age (i) some cautious drivers may perceive the risk of engaging in secondary tasks, thereby exhibiting shorter gaze durations, and (ii) some drivers exhibit risky behavior despite recognizing the risk of engaging in the secondary tasks, leading to longer gaze durations.

Discussion

With ever-increasing technological advancements facilitating newer vehicles, drivers' engagement in in-vehicle systems has seen a drastic increase, which could deteriorate driving behavior. Several studies have quantified in-vehicle systems' impact on reaction time, mental workload, braking behavior, and vehicle control (*18*). Engaging with in-vehicle systems can alternatively be viewed as engaging in and performing secondary tasks, which require drivers to divert their eyes away from the driving scene to perform the task, which could deteriorate their driving behavior. This deterioration has been confirmed to vary across different age groups and gender in recent studies (e.g., Sharma et al. [*73*]; Ali et al. [*91*]; Ali et al. [*96*]; Ali and Haque [*26*]). To this end, this study developed a correlated random parameters duration model, which was compared with a fixed parameters duration to elucidate the difference in conclusions/findings obtained from these two different modeling approaches.

Comparison of the Correlated Random Parameters Model with a Fixed Parameters Model

Although the inferences provided by a random parameters model have been widely acknowledged to vary from a fixed parameters model, this section elucidates the additional insights offered by a correlated random parameters model over a fixed parameters model. Some noteworthy observations from the comparison of two modeling approaches (random parameters versus fixed parameters) in the context of our study are summarized as follows:

- Both the random- (Table 4) and fixed parameters models (Table C1 in the Appendix/Supplemental Material) indicated that the mean of Age Group 1 was negative, implying that relative to Age Group 2, on average, Age Group 1 took more time in reverting their gaze to the driving scene. However, an additional insight offered by the random parameters model was that the majority of drivers took more time, but a substantial proportion of drivers (48%) also took less time—this finding could only be obtained using the random parameters model, whereas the fixed parameters model would suggest that, relative to Age Group 2, all drivers in Age Group 1 took more time in reverting their gaze to the driving scene.
- The fixed parameters model for Age Group 3 suggested that all drivers took more time in completing the secondary task compared with Age Group 2. However, the random parameters model negated this observation, suggesting that not all drivers in Age Group 3 took more time.
- The fixed parameters model suggested shorter TEORT for females compared with males, but the random parameters model showed that females in Age Group 1 took relatively less time compared with males in the same group.
- Lastly, the correlation between random parameters indicated the mixed effects of Age Groups 1 and 3 on TEORT relative to Age Group 2 (i.e., drivers in these groups may take a shorter or longer time to complete their secondary tasks). It would not have been possible to extract these data from a fixed parameters model.

Effect of Age on TEORT

Different age groups are likely to exhibit different gazing behavior; this was quantified through the developed random parameters duration model. To this end, the model allowed for the development of survival curves that facilitated comparing gazing behavior across different age groups. Survival curves (or the probability of not completing the secondary task) were computed using the Weibull survival function and parameter estimates of the model reported in Table 4. Specifically, using the mean values of the continuous explanatory variables and reference categories for the dummy explanatory variables, the probabilities of not completing the secondary task at t s were computed. Note that for the random parameters, survival curves were developed for the mean of the parameter and lower and upper bounds (i.e., lower bound: the lower limit of Age Group 1's coefficient, that is, mean $-$ 1.645 $\times$ standard deviation; upper bound: the upper limit of Age Group 1's coefficient, that is, mean + 1.645 $\times$ standard deviation).

Figure 8 illustrates that the probabilities of not completing the secondary task decreased with elapsed time. In general, the results indicated that drivers in Age Group 1 completed their secondary tasks earlier than Age Group 2 (see Figure 8*a*), thereby diverting their gaze back to the driving scene sooner. The probability of not completing the secondary task, for example, for Age Group 1 at 1 s was 65%, whereas the corresponding probability for Age Group 2 was 67%. It is evident from Figure 8*a* that drivers in Age Group 1 took about 2.85 s to complete their secondary task, whereas drivers in Age Group 2 took about 2.95 s, indicating the latter group's delayed reverting of gaze. These findings suggest that although both age groups lost track of the driving scene while performing the secondary tasks, Age Group 2 drivers took relatively more time to revert their gaze to the driving scene. Taking more time to complete the secondary task or reverting the gaze to the driving scene later implies that drivers were unaware of surrounding traffic and at high risk of engaging in safety-critical events (*97*), with their direct consequence on loss of situational awareness, delayed response to a situation, and the need for abrupt braking (*12*).

Several studies have investigated drivers' gaze duration when engaging in secondary tasks involving mobile

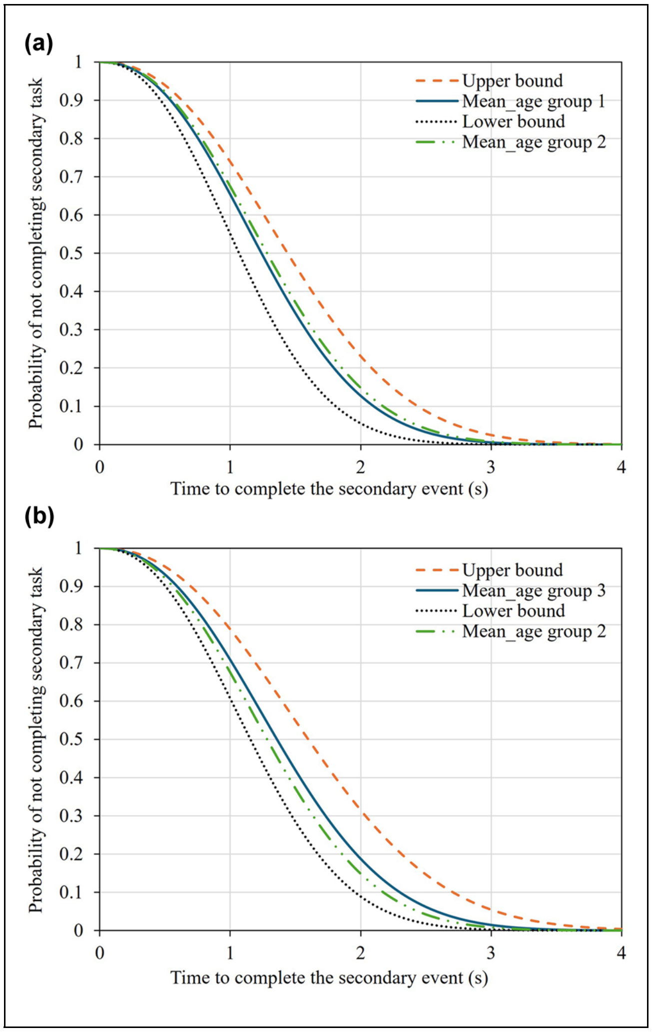


Figure 8. Secondary task completion probability for (*a*) Age Group 1 and (*b*) Age Group 3.

phones, navigation systems, in-vehicle displays, and so forth (*19*, *29*). While engaging with a speed limit advisory system provided by an in-vehicle human–machine interface, considering auditory perception characteristics in a connected environment, Xu et al. reported that drivers' total gaze duration (or glance in the original study) varied between 1.0 and 2.3 s (*67*). However, Xu et al.'s study did not explicitly mention the gaze duration of different age groups, despite having a diverse sample size. Heckman et al. analyzed drivers' visual behavior during vehicle reversing tasks and determined the factors affecting the use of rearview camera displays (*33*). They found that drivers between 18 and 39 years of age spent a larger proportion of time looking at the rearview displays compared with other age groups (40+ years), which contradicts our finding, that is, Age Group 1 (18 to 24 years) spent relatively less time on secondary tasks. This discrepancy can be explained in two ways. Firstly, the age group in Heckman et al.'s study included a wider age range (*33*). Secondly, the secondary task in their research was, as mentioned, reversing the vehicle using the rearview camera display, whereby attention to the front driving scene was relatively less important; this latter aspect was significantly different from our study, in which drivers were required to simultaneously complete the secondary task and control the vehicle (*33*). However, a study agreeing with our findings reported that young drivers (aged between 23 and 46 years) spent a lower amount of time using in-vehicle displays compared with other age groups (*98*). Although the age groups in Mourant et al.'s study and ours were dissimilar, the secondary task performed (looking at an in-vehicle display) was similar, resulting in complementary findings (*98*).

Age Groups 1 and 2 in our study represent the young and middle-aged drivers reported in several studies (e.g., Ali et al. [*99*]). In general, relative to middle-aged drivers, young drivers are novice, inexperienced, and have frequently been reported to exhibit risk-taking behavior, such as overtaking and speeding. Recognizing this risky behavior, a general notion is that young drivers tend to have longer gaze durations away from the driving scene, which contradicts our finding. However, this could be explained as follows: young drivers are generally tech-savvy and more familiar with navigation or other in-vehicle information systems, thereby taking a shorter time to complete the task compared with middle-aged drivers.

The random parameter for Age Group 1 also suggested that young drivers may take longer to complete the secondary task (or may take their gaze away for a longer time), indicating differential driver behavior. Despite young drivers being tech-savvy, they sometimes exhibit risk-taking behavior and take their eyes off the driving scene for relatively lengthy periods. Young drivers are often overconfident about their driving skills, which can lead to an overreliance on their capabilities to avoid any safety-critical events (*100*), as reflected in their longer gaze durations.

Comparing Age Groups 3 and 2, drivers in Age Group 3 completed their secondary tasks later than those in Age Group 2 (see Figure 8*b*), thereby diverting their gaze from the secondary task to the driving scene later. Relative to Age Group 2, the probability of not completing the secondary task for Age Group 3 at 1 s was 4% higher. Figure 8*b* suggests that drivers in Age Group 3 took about 0.17 s more time to complete their secondary task compared with Age Group 2, implying that drivers in Age Group 3 took relatively more time to revert their gaze to the driving scene. Those qualifying for Age Group 3 are generally termed "older drivers," and in the literature, they are reported to possess slower sensory motor/processing power, exhibit cautious driving behaviors, and to perceive task difficulty to be high, all

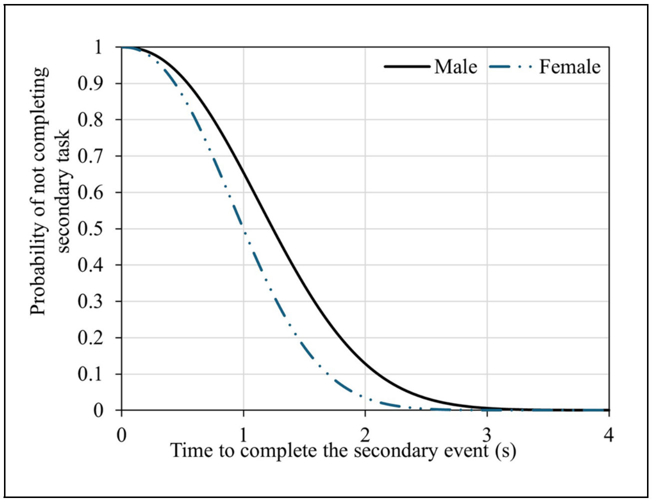


Figure 9. Secondary task completion probability for gender.

of which can lead to an increased crash risk (*101*, *102*). Zhu et al. investigated the association between older drivers' driving style and crash risk and found that older drivers who adopted a cautious driving style but were involved in traffic crashes had poorer visual acuity and -contrast sensitivity (*103*). These drivers are often not well-versed in technology and hesitant to use it, thereby often taking more time to complete such secondary tasks. Mourant et al. found that older drivers take longer to engage with in-vehicle information systems because they lack familiarity with the technology, which is reflected in their lengthier completion times for secondary tasks (*98*). Similar observations were made in our study, whereby older drivers took more time to revert their gaze to the driving scene, which could be risky and lead to safety-critical events. This raises concerns about the use of in-vehicle information systems by older drivers, despite the technologies' objective of improving driving behavior. Older drivers' reluctance to use technology, being slower in its adoption, and an over-reliance on their driving experience may not provide the desired outcome of these systems. As such, it is imperative that these systems are designed with these specific drivers in mind and tailored to their needs, similarly with the need to educate these drivers in using the technology.

Similar to Age Group 1, the random parameter for Age Group 3 also suggested that not all older drivers took longer to complete their secondary tasks: some older drivers may have benefited from their extensive driving experience, which made them risk-averse (*104*), thereby redirecting their gaze to the driving scene sooner.

Gender Difference in Gazing Behavior

Using the developed model, the survival curves for not completing the secondary task were developed (see Figure 9). For male drivers, the probability of not completing the secondary task at 1 s was 65%, whereas the corresponding probability for female drivers at the same point was 49%. This finding implied that male drivers were greater risk-takers than female drivers, and therefore more likely to engage in safety-critical events (*105*). Figure 9 illustrates that male drivers took about 2.85 s to complete their secondary task, whereas female drivers took about 2.3 s, indicating the delayed reversion of gaze to the driving scene by male drivers. Males are usually risk-takers, comply less with traffic norms, and commit more traffic offenses because of their biological-, psycho-social-, and impulsive behavior. McDonald et al. reported that male drivers are more likely to reoffend if their violation is classed as dangerous and careless driving, when compared with similar drivers penalized for other violations (e.g., seatbelt violations) (*106*).

Females are often risk-averse and take fewer risks than men during driving (*105*), leading to shorter gaze durations away from the driving scene. Females have been reported to be fluent with technology (*107*) and appear to complete the secondary task earlier than males. Female drivers perceive the risks of engaging in secondary tasks relatively more than men, which reflects their personal traits and driving attitudes (*108*).

Policy and Practice Implications

The developed model has provided several valuable insights to enhance safety in real-world situations and has practical implications for road authorities and wider stakeholders. Given that distracted drivers' approaching speed has detrimental effects on safety, lowering the speed limit in high workload areas coupled with strong monitoring and enforcement (e.g., using artificial intelligence-based CCTV and random mobile police checkpoints) would provide two benefits: (i) minimizing TEORT of distracted drivers, and (ii) harmonizing higher with lower speed traffic by minimizing the large speed variations applicable to both distracted and undistracted drivers—this could be achieved via variable speed limits. This application has shown safety benefits, for example, on the M1 motorway in the UK (*109*). Further, based on the study findings, tailored driver education programs should only be targeted at the young and at the female drivers to communicate the safety implications of secondary tasks. For instance, presenting a solution-driven theory test on explaining how collision probability increases when engaging in secondary tasks while driving would enforce the importance of minimizing secondary task involvement. Finally, implementing strong enforcement, for example, increasing demerit points and automatic cancellation of licenses (for young drivers), could also help to combat driver distraction.

Analyzing the effects of secondary tasks on gazing behavior provides an objective, quantitative measure for understanding crash risk, which could be used to design advanced driving assistance systems aimed at minimizing distractions and their consequent effects. For example, a recent study has highlighted that distraction feedback from warning-based advanced driver assistance systems (ADAS) effectively reduces instances of driver inattention, forward collisions, and lane departures (*110*). Notably, half of the monitored fleet experienced at least a 50% reduction in these warnings. In another study, lane departure warnings decreased within 2 months of ADAS usage, whereas warnings related to driver inattention and forward collisions dropped significantly after 6 months, thus recommending design systems that consider driving behavior in relation to spatiotemporal mechanisms (*111*).

Conclusions

This study investigated drivers' gaze duration away from the driving scene, characterized by TEORT, while engaged in secondary tasks, performed using in-vehicle information systems. Eighty-five licensed participants, aged between 18 and 65 years, were asked to perform secondary tasks on a suburban road in a simulated driving environment: University of Kansas driving simulator. The secondary tasks involved using a navigation system for traveling to a planned destination—a common task in our daily routines. A correlated grouped random parameters Weibull AFT model with heterogeneity in the mean was developed to model drivers' TEORT during the secondary tasks.

Overall, the modeling results indicated the heterogeneous gazing behavior of the two driving groups. The mean parameter of the young driver dummy variable (Age Group 1) implied that the majority of these drivers completed their secondary tasks earlier (or reverted their gaze to the driving scene earlier), suggesting safer behavior. However, some young drivers also took longer to complete their secondary tasks, reflecting longer gaze durations away from the driving scene, leading to a higher likelihood of engaging in safety-critical events. Similarly, the random parameter of older drivers (Age Group 3) indicated that gaze durations could increase or decrease: the lengthier durations were attributed to inexperience with technology, thereby taking more time to revert gaze to the driving scene (risky driving). In contrast, a small cohorot of Age Group 3 took less time to complete their secondary tasks, reflecting proactive driving behavior as these drivers, presumably, recognized the direct risks of taking their gaze away from the driving scene. Finally, females exhibited shorter gaze durations than males, reflecting their safety-conscious, risk-averse behavior. In addition to the aforementioned random parameters, three nonrandom parameters were also found to affect gaze duration: initial speed, speed fluctuations, and the number of kilometers driven. Drivers had shorter gaze durations when their initial speed was higher, exhibited large speed fluctuations, and drove a higher number of kilometers, mainly because of higher perceived crash risk.

The findings of our study could contribute significantly to the design of advanced driver assistance systems and to keeping the driver in the loop when they are not actively driving but must continuously monitor the system (e.g., in Levels 3 and 4 autonomous vehicles, in which drivers may be required to take control). The findings from this study could also help in designing adaptable in-vehicle notifications for drivers of different age groups and genders, given that their gaze durations were found to vary. As such, futuristic in-vehicle design will be human-centric rather than generic, thus catering to the needs of diverse users.

Unlike most driving simulator–based studies, in which driving behavior is compared in a relative manner (e.g., TEORT with and without mobile phone use), our study analyzed gaze durations in an isolated fashion, mainly because of a meaningless baseline condition in our context, that is, drivers would have zero TEORT if there were no secondary task to focus on.

As with all research, this study had limitations. It only compared TEORT when engaged in one type of secondary task and under a specific cognitive workload (for details, refer to Appendix A/Supplemental Material), thereby restricting us from performing a comparative analysis of varying gaze durations across different tasks. Therefore, associating gaze durations with the workload exerted by other secondary tasks merits investigation. Similarly, assessing TEORT during different driving tasks, such as merging and interacting with pedestrians, would provide a more complete picture of gazing behavior and its variations across driving tasks. Moreover, although this study evaluated gazing behavior in a high cognitive load environment, gradually elevating this cognitive load to determine the optimal point at which driving behavior starts to deteriorate would have significant value. This study also did not investigate how gazing behavior varies as a function of time of day and environmental conditions, which might lead to different gazing behavior, thus requiring a separate investigation. Finally, this study did not use any sophisticated techniques for capturing/testing all possible combinations of interaction terms in the model (e.g., a decision tree). Future studies could employ machine learning techniques to test all possible combinations in the model.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Y. Ali, V. C. Kummetha, A. Kondyli; data collection: V. C. Kummetha, A. Kondyli; analysis and interpretation of results: Y. Ali, V. C. Kummetha, A. Sharma, A. Kondyli; draft manuscript preparation: Y. Ali, V. C. Kummetha, A. Sharma, A. Kondyli. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The authors declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: Alexandra Kondyli is a member of *Transportation Research Record*'s editorial board.

Funding

The authors disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This work was supported by the Mid-America Transportation Center, Lincoln, NE (Grant no. 69A3551747107, 2017) in cooperation with the U.S. Department of Transportation, Federal Highway Administration.

ORCID iDs

Yasir Ali https://orcid.org/0000-0002-5770-0062
Vishal C. Kummetha https://orcid.org/0000-0001-9464-6838
Anshuman Sharma https://orcid.org/0000-0002-6838-0914
Alexandra Kondyli https://orcid.org/0000-0002-3462-0000

Data Accessibility Statement

The datasets generated during and/or analyzed during the study are not publicly available because they contain sensitive information that could compromise research participant privacy/consent, but they are available from the corresponding author on reasonable request.

Supplemental Material

Supplemental material for this article is available online.

References

1. Ali, Y., A. Sharma, and D. Chen. Investigating Autonomous Vehicle Discretionary Lane-Changing Execution Behaviour: Similarities, Differences, and Insights from Waymo Dataset. *Analytic Methods in Accident Research*, Vol. 42, 2024, p. 100332.
2. Ali, Y., A. Sharma, M. M. Haque, Z. Zheng, and M. Saifuzzaman. The Impact of the Connected Environment on Driving Behavior and Safety: A Driving Simulator Study. *Accident Analysis & Prevention*, Vol. 144, 2020, p. 105643.
3. Oviedo-Trespalacios, O., M. M. Haque, M. King, and S. Washington. Understanding the Impacts of Mobile Phone Distraction on Driving Performance: A Systematic Review. *Transportation Research Part C: Emerging Technologies*, Vol. 72, 2016, pp. 360–380.
4. Engström, J., E. Johansson, and J. Östlund. Effects of Visual and Cognitive Load in Real and Simulated Motorway Driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 8, No. 2, 2005, pp. 97–120.
5. Dingus, T. A., S. G. Klauer, V. L. Neale, A. Petersen, S. E. Lee, J. Sudweeks, M. A. Perez, J. Hankey, D. Ramsey, and S. Gupta. *The 100-Car Naturalistic Driving Study, Phase II-Results of the 100-Car Field Experiment*. United States Department of Transportation, National Highway Traffic Safety Adminstration, 2006.
6. NHTSA. *Distracted Driving*, Washington, D.C.https://www.nhtsa.gov/risky-driving/distracted-driving. Accessed June 16, 2023.
7. Statista. *Road Accidents: Contributory Factors in Great Britain*. https://www.statista.com/statistics/323093/road-accidents-caused-by-impairment-or-distraction-factors-severity-in-great-britain-uk/. Accessed February 22, 2023.
8. BITRE. *Road Safety Is Everyone's Responsibility*. https://minister.infrastructure.gov.au/brown/media-release/road-safety-everyones-responsibility#:~:text=The%20number%20of%20mobile%20phone,in%20hospital%20attendance%20in%20Australia. Accessed November 15, 2023.
9. Graab, B., E. Donner, U. Chiellino, and M. Hoppe. Analyse von Verkehrsunfällen hinsichtlich unterschiedlicher Fahrerpopulationen und daraus ableitbarer Ergebnisse für die Entwicklung adaptiver Fahrerassistenzsysteme. In *3. Tagung Aktive Sicherheit durch Fahrerassistenz*, 2008.
10. Song, D., J. Zhao, B. Zhu, J. Han, and S. Jia. Subjective Driving Risk Prediction Based on Spatiotemporal Distribution Features of Human Driver's Cognitive Risk. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 25, No. 11, 2024, pp. 16687–16703.
11. Horrey, W. J., and C. D. Wickens. Examining the Impact of Cell Phone Conversations on Driving Using Meta-Analytic Techniques. *Human Factors*, Vol. 48, No. 1, 2006, pp. 196–205.
12. Caird, J. K., C. R. Willness, P. Steel, and C. Scialfa. A Meta-Analysis of the Effects of Cell Phones on Driver Performance. *Accident Analysis & Prevention*, Vol. 40, No. 4, 2008, pp. 1282–1293.
13. Regan, M. A., J. D. Lee, and K. Young. *Driver Distraction: Theory, Effects, and Mitigation*. CRC Press, FL, 2008.
14. Ezzati Amini, R., C. Al Haddad, D. Batabyal, I. Gkena, B. De Vos, A. Cuenen, T. Brijs, and C. Antoniou. Driver Distraction and In-Vehicle Interventions: A Driving Simulator Study on Visual Attention and Driving Performance. *Accident Analysis & Prevention*, Vol. 191, 2023, p. 107195.
15. Topolšek, D., I. Areh, and T. Cvahte. Examination of Driver Detection of Roadside Traffic Signs and Advertisements Using Eye Tracking. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 43, 2016, pp. 212–224.
16. Kummetha, V. C., A. Kondyli, and H. Devos. Evaluating Driver Comprehension of the Roadway Environment to Retain Accountability of Safety During Driving Automation. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 81, 2021, pp. 457–471.

17. Zeeb, K., A. Buchner, and M. Schrauf. What Determines the Take-Over Time? An Integrated Model Approach of Driver Take-Over After Automated Driving. *Accident Analysis & Prevention*, Vol. 78, 2015, pp. 212–221.
18. Yared, T., P. Patterson, and A. Mumani. Distraction and Visual Search Characteristics of Young Drivers When Using Navigation System Displays. *Journal of Engineering Research*, Vol. 12, No. 3, 2023, pp. 484–493.
19. Maciej, J., and M. Vollrath. Comparison of Manual vs. Speech-Based Interaction With In-Vehicle Information Systems. *Accident Analysis & Prevention*, Vol. 41, No. 5, 2009, pp. 924–930.
20. Garrison, T. M., and C. C. Williams. Impact of Relevance and Distraction on Driving Performance and Visual Attention in a Simulated Driving Environment. *Applied Cognitive Psychology*, Vol. 27, No. 3, 2013, pp. 396–405.
21. Cooper, J. M., C. L. Wheatley, M. M. Horrey, C. J. McCarty, C. L. Motzkus, G. G. Lopes, B. R. Erickson, W. J. Baucom, and D. L. Strayer. Age-Related Differences in the Cognitive, Visual, and Temporal Demands of In-Vehicle Information Systems. *Frontiers in Psychology*, Vol. 11, 2020, p. 1154.
22. Islam, S., and F. Mannering. Driver Aging and Its Effect on Male and Female Single-Vehicle Accident Injuries: Some Additional Evidence. *Journal of Safety Research*, Vol. 37, No. 3, 2006, pp. 267–276.
23. Turner, C., and R. McClure. Age and Gender Differences in Risk-Taking Behaviour as an Explanation for High Incidence of Motor Vehicle Crashes as a Driver in Young Males. *Injury Control and Safety Promotion*, Vol. 10, No. 3, 2003, pp. 123–130.
24. Swedler, D. I., S. M. Bowman, and S. P. Baker. Gender and Age Differences Among Teen Drivers in Fatal Crashes. In *Annals of Advances in Automotive Medicine/Annual Scientific Conference, No. 56*. Association for the Advancement of Automotive Medicine, Chicago, 2012, p. 97.
25. Regev, S., J. J. Rolison, and S. Moutari. Crash Risk by Driver Age, Gender, and Time of Day Using a New Exposure Methodology. *Journal of Safety Research*, Vol. 66, 2018, pp. 131–140.
26. Ali, Y., and M. M. Haque. Modelling Braking Behaviour of Distracted Young Drivers in Car-Following Interactions: A Grouped Random Parameters Duration Model with Heterogeneity-In-Means. *Accident Analysis & Prevention*, Vol. 185, 2023, p. 107015.
27. Wikman, A.-S., T. Nieminen, and H. Summala. Driving Experience and Time-Sharing during In-Car Tasks on Roads of Different Width. *Ergonomics*, Vol. 41, No. 3, 1998, pp. 358–372.
28. Bachfischer, K., C. Waeller, S. Troesterer, A. Tatzel, and F. P. Leon. Eye Gaze and Movement Behaviour in the Operation of Adaptive In-Car Touchscreens. *In 2008 IEEE Intelligent Vehicles Symposium* (H. Nijmeijer and B. v. Arem, eds), Eindhoven, The Netherlands. IEEE, 2008, pp. 1027–1032.
29. Rakotonirainy, A., F. Feller, and N. Haworth. Using in-Vehicle Avatars to Prevent Road Violence. In *Adjunct Proceedings of Pervasive 2008: The Sixth International Conference on Pervasive Computing* (J. Indulska, D. J. Patterson, T. R. M. Ott, eds), Springer, Sydney, Australia, 2008, pp. 70–74.
30. Kim, S., and A. K. Dey. Simulated Augmented Reality Windshield Display as a Cognitive Mapping Aid for Elder Driver Navigation. In *Proc. SIGCHI Conference on Human Factors in Computing Systems* (D. R. Olsen, R. B. Arthur, K. Hinckley, M. R. Morris, S. E. Hudson, S. Greenberg, eds), Boston, 2009, pp. 133–142.
31. Perez, M., D. Viita, S. Voran-Nowak, and S. Tengler. On-Road Evaluation of Destination Entry and Way-Finding Tasks: Comparisons Against Normal Driving. In *Driving Assessment Conference, No. 6* (S. R. (Shel) Schlanger, ed.), University of Iowa, Reno, 2011.
32. Pradhan, A. K., G. Divekar, K. Masserang, M. Romoser, T. Zafian, R. D. Blomberg, F. D. Thomas, I. Reagan, M. Knodler, and A. Pollatsek. The Effects of Focused Attention Training on the Duration of Novice Drivers' Glances Inside the Vehicle. *Ergonomics*, Vol. 54, No. 10, 2011, pp. 917–931.
33. Heckman, G. M., R. S. Kim, S. Lin, R. Rauschenberger, D. E. Young, and R. Lange. Drivers' Visual Behavior During Backing Tasks: Factors Affecting the Use of Rearview Camera Displays. In *Proc. Human Factors and Ergonomics Society Annual Meeting, No. 56*. SAGE, Los Angeles, CA, 2012, pp. 2236–2240.
34. Neurauter, M. L., J. M. Hankey, T. B. Schalk, and G. Wallace. Outbound Texting: Comparison of Speech-Based Approach and Handheld Touch-Screen Equivalent. *Transportation Research Record*, Vol. 2321, No. 1, 2012, pp. 23–30.
35. Hirayama, T., K. Mase, and K. Takeda. Analysis of Temporal Relationships Between Eye Gaze and Peripheral Vehicle Behavior for Detecting Driver Distraction. *International Journal of Vehicular Technology*, Vol. 2013, p. 285927.
36. Olaverri-Monreal, C., A. E. Hasan, J. Bulut, M. Körber, and K. Bengler. Impact of In-Vehicle Displays Location Preferences on Drivers' Performance and Gaze. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 15, No. 4, 2014, pp. 1770–1780.
37. Soccolich, S. A., G. M. Fitch, M. A. Perez, and R. J. Hanowski. Comparing Handheld and Hands-Free Cell Phone Usage Behaviors While Driving. *Traffic Injury Prevention*, Vol. 15, No. Suppl. 1, 2014, pp. S21–S26.
38. Fitch, G. M., P. R. Bartholomew, R. J. Hanowski, and M. A. Perez. Drivers' Visual Behavior When Using Handheld and Hands-Free Cell Phones. *Journal of Safety Research*, Vol. 54, 2015, pp. 105.e129–108.
39. Mehler, B., D. Kidd, B. Reimer, I. Reagan, J. Dobres, and A. McCartt. Multi-Modal Assessment of On-Road Demand of Voice and Manual Phone Calling and Voice Navigation Entry Across Two Embedded Vehicle Systems. *Ergonomics*, Vol. 59, No. 3, 2016, pp. 344–367.
40. Carney, C., K. K. Harland, and D. V. McGehee. Using Event-Triggered Naturalistic Data to Examine the Prevalence of Teen Driver Distractions in Rear-End Crashes. *Journal of Safety Research*, Vol. 57, 2016, pp. 47–52.
41. Hurtado, S., and S. Chiasson. An Eye-Tracking Evaluation of Driver Distraction and Unfamiliar Road Signs. In *Proc.*

8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications (P. Green, S. C. J. Boll, J. Gabbard, S. Osswald, G. Burnett, eds), Ann Harbor, MI, 2016, pp. 153–160.
42. Large, D. R., E. Crundall, G. Burnett, C. Harvey, and P. Konstantopoulos. Driving Without Wings: The Effect of Different Digital Mirror Locations on the Visual Behaviour, Performance and Opinions of Drivers. *Applied Ergonomics*, Vol. 55, 2016, pp. 138–148.
43. Louveton, N., R. Mccall, V. Koenig, T. Avanesov, and T. Engel. Driving While Using a Smartphone-Based Mobility Application: Evaluating the Impact of Three Multi-Choice User Interfaces on Visual-Manual Distraction. *Applied Ergonomics*, Vol. 54, 2016, pp. 196–204.
44. Munoz, M., B. Reimer, J. Lee, B. Mehler, and L. Fridman. Distinguishing Patterns in Drivers' Visual Attention Allocation Using Hidden Markov Models. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 43, 2016, pp. 90–103.
45. Reimer, B., B. Mehler, I. Reagan, D. Kidd, and J. Dobres. Multi-Modal Demands of a Smartphone Used to Place Calls and Enter Addresses During Highway Driving Relative to Two Embedded Systems. *Ergonomics*, Vol. 59, No. 12, 2016, pp. 1565–1585.
46. Purucker, C., F. Naujoks, A. Prill, and A. Neukum. Evaluating Distraction of In-Vehicle Information Systems While Driving by Predicting Total Eyes-Off-Road Times with Keystroke Level Modeling. *Applied Ergonomics*, Vol. 58, 2017, pp. 543–554.
47. Kaufmann, P., and A. Riener. Evaluation of Driving Performance and User Experience of Different Types of Speedometer. In *Adjunct Proceedings of the 10th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, Toronto, Canada, 2018, pp. 110–114.
48. Liu, S.-Y., J. D. Lee, J. Y. Lee, and V. Venkatraman. Glances That Matter: Applying Quantile Regression to Assess Driver Distraction from Off-Road Glances. In *Proc. Human Factors and Ergonomics Society Annual Meeting, No. 62*, SAGE, Los Angeles, CA, 2018, pp. 1954–1958.
49. McWilliams, T., N. Ward, B. Mehler, and B. Reimer. Assessing Driving Simulator Validity: A Comparison of Multi-Modal Smartphone Interactions Across Simulated and Field Environments. *Transportation Research Record*, Vol. 2672, No. 37, 2018, pp. 164–171.
50. Naujoks, F., S. Höfling, C. Purucker, and K. Zeeb. From Partial and High Automation to Manual Driving: Relationship Between Non-Driving Related Tasks, Drowsiness and Take-Over Performance. *Accident Analysis & Prevention*, Vol. 121, 2018, pp. 28–42.
51. Biondi, F. N., D. Getty, J. M. Cooper, and D. L. Strayer. Examining the Effect of Infotainment Auditory-Vocal Systems' Design Components on Workload and Usability. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 62, 2019, pp. 520–528.
52. Jeihani, M., S. Ahangari, A. Hassan Pour, N. Khadem, and S. Banerjee. *Investigating the Impact of Distracted Driving among Different Socio-Demographic Groups.* Department of Transportation, MD, University Transportation Centers (UTC) Program, Virginia Tech Transportation Institute, 2019.
53. Jeong, H., and Y. Liu. Effects of Non-Driving-Related-Task Modality and Road Geometry on Eye Movements, Lane-Keeping Performance, and Workload While Driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 60, 2019, pp. 157–171.
54. He, D., and B. Donmez. Influence of Driving Experience on Distraction Engagement in Automated Vehicles. *Transportation Research Record*, Vol. 2673, No. 9, 2019, pp. 142–151.
55. Miller, E. E., and L. N. Boyle. Adaptations in Attention Allocation: Implications for Takeover in an Automated Vehicle. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 66, 2019, pp. 101–110.
56. Reagan, I. J., D. G. Kidd, J. Dobres, B. Mehler, and B. Reimer. The Effects of Age, Interface Modality, and System Design on Drivers' Attentional Demand When Making Phone Calls While Driving on a Limited-Access Highway. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 60, 2019, pp. 536–548.
57. Kohl, J., A. Gross, M. Henning, and T. Baumgarten. Driver Glance Behavior Towards Displayed Images on In-Vehicle Information Systems Under Real Driving Conditions. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 70, 2020, pp. 163–174.
58. Gomaa, A., G. Reyes, A. Alles, L. Rupp, and M. Feld. Studying Person-Specific Pointing and Gaze Behavior for Multimodal Referencing of Outside Objects from a Moving Vehicle. In *Proc. 2020 International Conference on Multimodal Interaction* (K. Truong, D. Heylen, M. Czerwinski, eds), ICMI, New York, 2020, pp. 501–509.
59. Wang, X., R. Xu, A. Asmelash, Y. Xing, and C. Lee. Characteristics of Driver Cell Phone Use and Their Influence on Driving Performance: A Naturalistic Driving Study. *Accident Analysis & Prevention*, Vol. 148, 2020, p. 105845.
60. Abbasi, J. A., D. Mullins, N. Ringelstein, P. Reilhac, E. Jones, and M. Glavin. An Analysis of Driver Gaze Behaviour at Roundabouts. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 23, No. 7, 2021, pp. 8715–8724.
61. Li, X., R. Schroeter, A. Rakotonirainy, J. Kuo, and M. G. Lenné. Get Ready for Take-Overs: Using Head-Up Display for Drivers to Engage in Non–Driving-Related Tasks in Automated Vehicles. *Human Factors*, Vol. 65, No. 8, 2021, p. 00187208211056200.
62. Noble, A. M., M. Miles, M. A. Perez, F. Guo, and S. G. Klauer. Evaluating Driver Eye Glance Behavior and Secondary Task Engagement While Using Driving Automation Systems. *Accident Analysis & Prevention*, Vol. 151, 2021, p. 105959.
63. Turnbull, P. R., S. Khanal, and S. C. Dakin. The Effect of Cellphone Position on Driving and Gaze Behaviour. *Scientific Reports*, Vol. 11, No. 1, 2021, pp. 1–10.
64. Yang, S., J. Kuo, and M. G. Lenné. Effects of Distraction in on-Road Level 2 Automated Driving: Impacts on Glance Behavior and Takeover Performance. *Human Factors*, Vol. 63, No. 8, 2021, pp. 1485–1497.

65. Shabani, S., S. Beauchemin, and M. Bauer. Analysis of Driver Gaze and Attention to Traffic Signs. *Journal of Advanced Transportation*, Vol. 2022, pp. 1–13.
66. Monk, C., R. Sall, B. D. Lester, and J. S. Higgins. Visual and Cognitive Demands of Manual and Voice-Based Driving Mode Implementations on Smartphones. *Accident Analysis & Prevention*, Vol. 187, 2023, p. 107033.
67. Xu, Q., R. Fu, F. Wu, B. Wang, and T. Chen. A Speed Limit Advisory System Provided by In-Vehicle HMI Considering Auditory Perception Characteristics for Connected Environment. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 92, 2023, pp. 353–368.
68. Zhang, F., and S. C. Roberts. Factors Affecting Drivers' Off-Road Glance Behavior While Interacting with In-Vehicle Voice Interfaces. *Accident Analysis & Prevention*, Vol. 179, 2023, p. 106883.
69. Zhao, X., Z. Li, C. Zhao, C. Wang, and R. Fu. Distraction Pattern Classification and Comparisons Under Different Conditions in the Full-Touch HMI Mode. *Displays*, Vol. 78, 2023, p. 102413.
70. Ma, J., J. Li, W. Wang, H. Huang, X. Zhang, and J. Zhao. The Impact of Co-Pilot Displays Use on Driver Workload and Driving Performance Exploring the Impact of Co-Pilot Display on Drivers' Workload and Driving Performance. *Applied Ergonomics*, Vol. 114, 2024, p. 104138.
71. Hu, J., H. Jiang, D. Liu, Z. Xiao, Q. Zhang, G. Min, and J. Liu. Real-Time Contactless Eye Blink Detection Using UWB Radar. *IEEE Transactions on Mobile Computing*, Vol. 23, No. 6, 2023, pp. 6606–6619.
72. Shiferaw, B., C. Stough, and L. Downey. Drivers' Visual Scanning Impairment under the Influences of Alcohol and Distraction: A Literature Review. *Current Drug Abuse Reviews*, Vol. 7, No. 3, 2014, pp. 174–182.
73. Sharma, A., Z. Zheng, J. Kim, A. Bhaskar, and M. M. Haque. Is an Informed Driver a Better Decision Maker? A Grouped Random Parameters with Heterogeneity-In-Means Approach to Investigate the Impact of the Connected Environment on Driving Behaviour in Safety-Critical Situations. *Analytic Methods in Accident Research*, Vol. 27, 2020, p. 100127.
74. Ali, Y., M. C. Bliemer, Z. Zheng, and M. M. Haque. Cooperate or Not? Exploring Drivers' Interactions and Response Times to a Lane-Changing Request in a Connected Environment. *Transportation Research Part C: Emerging Technologies*, Vol. 120, 2020, p. 102816.
75. Ali, Y., M. M. Haque, Z. Zheng, and A. P. Afghari. A Bayesian Correlated Grouped Random Parameters Duration Model with Heterogeneity in the Means for Understanding Braking Behaviour in a Connected Environment. *Analytic Methods in Accident Research*, Vol. 35, 2022, p. 100221.
76. Ali, Y., Z. Zheng, M. M. Haque, M. Yildirimoglu, and S. Washington. Detecting, Analysing, and Modelling Failed Lane-Changing Attempts in Traditional and Connected Environments. *Analytic Methods in Accident Research*, Vol. 28, 2020, p. 100138.
77. Alnawmasi, N., and F. Mannering. A Statistical Assessment of Temporal Instability in the Factors Determining Motorcyclist Injury Severities. *Analytic Methods in Accident Research*, Vol. 22, 2019, p. 100090.
78. Brookhuis, K. A., G. de Vries, and D. De Waard. The Effects of Mobile Telephoning on Driving Performance. *Accident Analysis & Prevention*, Vol. 23, No. 4, 1991, pp. 309–316.
79. Gershon, P., A. Ronen, T. Oron-Gilad, and D. Shinar. The Effects of an Interactive Cognitive Task (ICT) in Suppressing Fatigue Symptoms in Driving. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 12, No. 1, 2009, pp. 21–28.
80. Atchley, P., and M. Chan. Potential Benefits and Costs of Concurrent Task Engagement to Maintain Vigilance: A Driving Simulator Investigation. *Human Factors*, Vol. 53, No. 1, 2011, pp. 3–12.
81. Nijboer, M., J. P. Borst, H. Van Rijn, and N. A. Taatgen. Driving and Multitasking: The Good, the Bad, and the Dangerous. *Frontiers in Psychology*, Vol. 7, 2016, p. 1718.
82. The National Advanced Driving Simulator. MiniSim User's Guide. In *Document Version 19*. Iowa City, IA, 2015.
83. Eye Tracking Inc. *EyeWorks 3 User Manual*. Eye Tracking Inc., Solana Beach, CA, 2019.
84. Kummetha, V. C., and A. Kondyli. Simulator-Based Framework to Incorporate Driving Heterogeneity via a Biobehavioral Extension to the Intelligent Driver Model. *Transportation Research Record*, Vol. 2677, No. 5, 2022, p. 03611981221134630.
85. Kummetha, V. C., A. Kondyli, E. G. Chrysikou, and S. D. Schrock. Safety Analysis of Work Zone Complexity with Respect to Driver Characteristics — A Simulator Study Employing Performance and Gaze Measures. *Accident Analysis & Prevention*, Vol. 142, 2020, p. 105566.
86. Kummetha, V. C. Incorporating Biobehavioral Architecture into Car-Following Models: A Driving Simulator Study. In *Civil, Environmental, and Architectural Engineering, PhD Dissertation*. University of Kansas, 2020.
87. Hart, S. G. *NASA Task Load Index (TLX)*. NASA Ames Research Center, CA, 1986.
88. Selcon, S. J., and R. Taylor. Evaluation of the Situational Awareness Rating Technique (SART) as a Tool for Aircrew Systems Design. *AGARD, Situational Awareness in Aerospace Operations (SEE N 90-28972 23-53)*, 1990.
89. Washington, S., M. Karlaftis, F. Mannering, and P. Anastasopoulos. *Statistical and Econometric Methods for Transportation Data Analysis*, Chapman and Hall/CRC, New York, 2020.
90. Haque, M. M., and S. Washington. A Parametric Duration Model of the Reaction Times of Drivers Distracted by Mobile Phone Conversations. *Accident Analysis & Prevention*, Vol. 62, 2014, pp. 42–53.
91. Ali, Y., Z. Zheng, and M. M. Haque. Modelling Lane-Changing Execution Behaviour in a Connected Environment: A Grouped Random Parameters with Heterogeneity-In-Means Approach. *Communications in Transportation Research*, Vol. 1, 2021, p. 100009.
92. Greene, W. LIMDEP Version 10/NLOGIT Version 5. In *Econometric Modeling Guide*. 2012.

93. Fountas, G., P. Anastasopoulos, and M. Abdel-Aty. Analysis of Accident Injury-Severities Using a Correlated Random Parameters Ordered Probit Approach with Time Variant Covariates. *Analytic Methods in Accident Research*, Vol. 18, 2018, pp. 57–68.
94. Bhat, C. R. Simulation Estimation of Mixed Discrete Choice Models Using Randomized and Scrambled Halton Sequences. *Transportation Research Part B: Methodological*, Vol. 37, No. 9, 2003, pp. 837–855.
95. Mannering, F., V. Shankar, and C. Bhat. Unobserved Heterogeneity and the Statistical Analysis of Highway Accident Data. *Analytic Methods in Accident Research*, Vol. 11, 2016, pp. 1–16.
96. Ali, Y., M. Haque, Z. Zheng, and A. Afghari. A Bayesian Correlated Grouped Random Parameters Duration Model with Heterogeneity in the Means for Understanding Braking Behaviour in a Connected Environment. *Analytic Methods in Accident Research*, Vol. 35, 2022, p. 100221.
97. Ali, Y., M. P. H. Raadsen, and M. C. J. Bliemer. Modelling speed reduction behaviour on variable speed limit-controlled highways considering surrounding traffic pressure: A random parameters duration modelling approach. *Analytic methods in accident research*, Vol. 40, 2023, p. 100290.
98. Mourant, R. R., F.-J. Tsai, T. Al-Shihabi, and B. K. Jaeger. Measuring the Divided Attention Capability of Young and Older Drivers. *Transportation Research Record: Journal of the Transportation Research Board*, Vol. 1779, 2001, pp. 40–45.
99. Ali, Y., M. M. Haque, Z. Zheng, S. Washington, and M. Yildirimoglu. A Hazard-Based Duration Model to Quantify the Impact of Connected Driving Environment on Safety During Mandatory Lane-Changing. *Transportation Research Part C: Emerging Technologies*, Vol. 106, 2019, pp. 113–131.
100. Ali, Y., Z. Zheng, M. M. Haque, M. Yildirimoglu, and S. Washington. Understanding the Discretionary Lane-Changing Behaviour in the Connected Environment. *Accident Analysis & Prevention*, Vol. 137, 2020, p. 105463.
101. Karthaus, M., and M. Falkenstein. Functional Changes and Driving Performance in Older Drivers: Assessment and Interventions. *Geriatrics*, Vol. 1, No. 2, 2016, p. 12.
102. Salvia, E., C. Petit, S. Champely, R. Chomette, F. Di Rienzo, and C. Collet. Effects of Age and Task Load on Drivers' Response Accuracy and Reaction Time When Responding to Traffic Lights. *Frontiers in Aging Neuroscience*, Vol. 8, 2016, p. 169.
103. Zhu, Y., M. Jiang, and T. Yamamoto. Does a Cautious Driving Style Reduce the Crash Risk of Older Drivers? An Analysis Using a Novel Driving Style Recognition Method. *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 104, 2024, pp. 72–87.
104. Finn, P., and B. W. Bragg. Perception of the Risk of an Accident by Young and Older Drivers. *Accident Analysis & Prevention*, Vol. 18, No. 4, 1986, pp. 289–298.
105. Montgomery, J., K. D. Kusano, and H. C. Gabler. Age and Gender Differences in Time to Collision at Braking from the 100-Car Naturalistic Driving Study. *Traffic Injury Prevention*, Vol. 15, No. Suppl. 1, 2014, pp. S15–S20.
106. McDonald, H., J. Berecki-Gisolf, K. Stephan, and S. Newstead. Traffic Offending and Deterrence: An Examination of Recidivism Amongst Drivers in Victoria, Australia Born Prior to 1975. *PLoS One*, Vol. 15, No. 10, 2020, p. e0239942.
107. Feys, M., E. Rombaut, and L. Vanhaverbeke. Does a Test Ride Influence Attitude Towards Autonomous Vehicles? A Field Experiment with Pretest and Posttest Measurement. *Sustainability*, Vol. 13, No. 10, 2021, p. 5387.
108. Fraschetti, A., P. Cordellieri, G. Lausi, E. Mari, E. Paoli, J. Burrai, A. Quaglieri, M. Baldi, A. Pizzo, and A. M. Giannini. Mobile Phone Use "on the Road": A Self-Report Study on Young Drivers. *Frontiers in Psychology*, Vol. 12, 2021, p. 620653.
109. National Highways. *M6 and M1 Safety Reviews*. https://nationalhighways.co.uk/our-work/smart-motorways-evidence-stocktake/m6-and-m1-safety-reviews/. Accessed June 1, 2024.
110. Masello, L., B. Sheehan, G. Castignani, D. Shannon, and F. Murphy. On the Impact of Advanced Driver Assistance Systems on Driving Distraction and Risky Behaviour: An Empirical Analysis of Irish Commercial Drivers. *Accident Analysis & Prevention*, Vol. 183, 2023, p. 106969.
111. Song, D., B. Zhu, J. Zhao, and J. Han. Modeling Lane-Changing Spatiotemporal Features Based on the Driving Behavior Generation Mechanism of Human Drivers. *Expert Systems with Applications*, Vol. 284, 2025, p. 127974.