A Framework for Adapting In-Car Touchscreen Interfaces to Driver Behaviors, Perception, and Cognition

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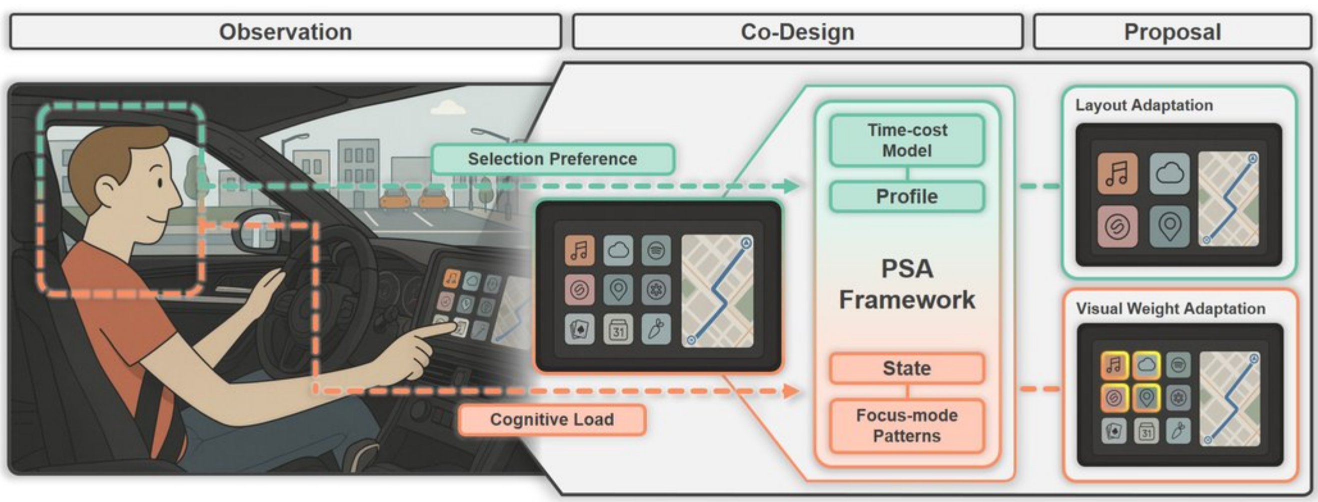

Figure 1: Conceptual diagram of the proposed Profile–State Adaptive (PSA) framework. Developed through three phases (Observation, Co-design, and Proposal), it illustrates how driver profile (selection patterns) and driver state (cognitive load) are extracted to adapt the in-vehicle touchscreen interface.

Abstract

Although in-car touchscreens expand interaction possibilities, they risk compromising driver safety and vigilance. We propose a data- and expert-informed framework for designing adaptive touchscreens that respond to a driver's usage profile and cognitive state, maximizing usability while mitigating safety risks. First, in a driving simulator study, we find that cognitive load slows touchscreen button selections by 20% and produced shorter, more frequent off-road glances. We also find that enlarging buttons improves selection speeds by 0.3 seconds but at the cost of requiring more display pages. Next, these findings informed a co-design session with expert in-cabin designers, generating guidelines for adaptive interfaces that balance usability and safety. These guidelines form the basis

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of our Profile-State Adaptive (PSA) framework, which integrates driver profiles with cognitive states to guide interface adaptations. We then extend the framework to include a quantitative Time-Cost model as well as design patterns for adaptive layouts across usage profiles and cognitive demands.

CCS Concepts

• **Human-centered computing → Touch screens**; **Interaction design process and methods**; *Empirical studies in interaction design.*

Keywords

Adaptive User Interfaces, Automotive User Interfaces, Cognitive Load, Driver Distraction, Touchscreen Interaction, Eye Tracking

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1 Introduction

Modern cars integrate navigation, communication, entertainment, and advanced driver assistance into unified displays and controls, thereby offering drivers a broad range of functions. As large touchscreens proliferate, flexible interface layouts support this broad range of functions. However, integrating multiple functions into touchscreens while removing physical buttons reduces tactile guidance and raises safety concerns. When driving, limited visual-cognitive resources are split between the road and secondary tasks, and even brief, well-timed glances can elevate risk [36, 43, 85, 86]. To address these issues, adaptive in-cabin interfaces have been proposed that adapt to a driver's context and cognitive state to minimize distractions and reduce touch and gaze demands.

Adaptive user interfaces are broadly defined as systems that adjust displays and available actions to match a user's present goals and abilities [95]. Prior studies have shown that adaptive user interfaces can improve user interaction with a system, including through facilitating system use, minimizing the need for help requests, helping manage complex systems, and preventing cognitive overload [22, 100, 104]. Vehicle research into adaptive user interfaces has primarily focused on optimizing recommendation algorithms for touchscreen UI elements, particularly by promoting frequently used functions to upper screen regions based on contextual relevance or by simplifying or disabling certain features [2, 32, 59, 70, 88, 102]. These approaches have proven effective in reducing driver distraction by lowering the number of interactions required during driving.

Prior research emphasizes that safe and effective in-vehicle UI design requires consideration of *for whom* and *under what circumstances*, and various computational models have been applied to predict or explain driver behavior in traditional static UIs (e.g., *Adaptive Control of Thought-Rational (ACT-R)* [4] and *Goals, Operations, Methods, and Selection Rules (GOMS)* [14, 56, 89]). However, these models prioritize behavior prediction within static settings rather than adaptive systems that dynamically account for a driver's state or context. They also do not provide practical design guidelines or tools [74]. Moreover, translating these considerations into adaptive user interfaces requires balancing adaptability against stability so that a system adapts its display and interaction methods to a user's cognitive state and context without undermining user expectations. Indeed, because adaptive user interfaces alter a system's behavior, they can reduce predictability and consistency, which may jeopardize a system's usability and ultimately driver safety. A practical design framework for in-vehicle adaptive user interfaces that accounts for both driver characteristics and driving context remains a current research gap. Motivated by this gap, our work introduces the Profile-State Adaptive (PSA) framework for guiding development of in-vehicle adaptive user interfaces, which we develop in a three-phase approach: through *Observation, Co-Design, and Proposal.*

In the **Observation phase**, we measured how drivers use an in-car touchscreen (similar to Android Auto [72]) under different cognitive load levels and UI configurations (button size, number of items, pagination). We confirmed that higher cognitive load slows touch selection and leads drivers to alternate their gaze between the road and the screen more frequently, and for shorter time periods. We also observed a layout tradeoff: larger and fewer items across multiple pages facilitate interactions with on-screen items but hinder access to items on other pages. In the **Co-Design phase**, we worked with experienced in-vehicle UI designers to turn these findings into principles for adaptive UIs. The experts emphasized: (1) adaptations should balance stability and adaptability, so drivers can predict where things are in the interface; (2) some adaptations should reflect a user's long-term preference *profile*, while others should react to the current situation *state*; and (3) touch and gaze effort should be kept low, such as by keeping a few fixed anchors. These ideas shaped the core policies of our Profile-State Adaptive (PSA) framework. In the **Proposal phase**, we then show how these policies can be implemented. For *profile-level adaptation*, we use an empirical *Time-Cost model* to choose layouts that match a driver's button-use pattern under different cognitive load conditions, using an expected-value-based formulation [3, 33, 106]. For *state-level adaptation*, we suggest *design patterns* that increase the salience of important controls without relocating targets, using small animations and gating rules so that adaptations do not interfere with driving.

The contributions of this work are as follows:

- Empirical quantification of how cognitive load and interface layout jointly shape touch performance and gaze behavior in a driving simulator.
- The *Profile-State Adaptive (PSA)* framework, which includes:
  (1) Co-design-informed *policies* that reconcile adaptability with stability via long-term profile-based structure and short-term state-based surface-level cosmetic adaptations.
  (2) A principled *Time-Cost model* that operationalizes profile-based layout selection using observed selection-time functions and driver-specific usage distributions.

(3) *Design patterns* for state-based adaptation that reduce search burden without relocating targets, preserving spatial predictability during driving.

2 Related Work

This section reviews prior research on driver cognitive load, in-vehicle touchscreen design, and adaptive automotive user interfaces.

2.1 Effects of Driver Cognitive Load

Cognitive load is an important topic in driving research [11], particularly in efforts to detect and reduce safety risks of distracted driving. Studies in real-world and simulated driving environments find that high cognitive load reduces people's attention to cues in their surrounding environment and increases unsafe behaviors [5, 12, 25, 39, 45, 93]. For example, an on-road study by Harbluk et al. [45] found that drivers who are performing a mental arithmetic task focus their gaze primarily on the center of the road. This shift in gaze led drivers to ignore peripheral cues in their mirrors or at intersections and increased frequency of dangerous hard-braking events. A meta-analysis by Caird et al. [12] found that conversations while driving (i.e., on a phone, with a passenger) lower vigilance to external events, slow driver reaction times, and increase risk of collisions.

In response to driving safety risks, regulators have proposed legislation mandating in-vehicle systems that detect and mitigate cognitive distraction [16]. In parallel, researchers have explored design interventions aimed at reducing cognitive demands, including haptic feedback [107, 108], driving difficulty prediction [34, 35], user interface design [1, 35, 68, 112], and input interaction techniques [13, 41, 44, 109]. For instance, Wang et al. [107, 108] applied haptic guidance torque on the steering wheel to reduce lane departure risks and Galarza et al. [34, 35] adapted interface functionality to anticipated driving complexity in on-road contexts. Other work has investigated interface modalities that reduce visual and cognitive demands of secondary tasks. Off-road glances and perceived workload can be reduced with approaches such as combining head-up displays (HUDs) with auditory earcons and gestures [13], designing low-visual-demand user interfaces [109], and employing gestures as alternatives to touch input [41, 44].

In sum, many factors can elevate cognitive load, deplete attentional resources, and constrain driver capacity to respond effectively. Actionable guidelines for closed-loop, adaptive touchscreen interaction design derived from driver behavior could help manage both visual distraction and cognitive demand.

2.2 Effects of In-Vehicle Touchscreens

In-vehicle touchscreens offer entertainment and navigation functions that enrich the driving experience. However, the growing number of functional interfaces has raised concerns about increased cognitive and visual demands, which may overload drivers and compromise safety [71]. Prior research has therefore examined how aspects of in-car touchscreen interactions (e.g., layout, target size, spatial organization) affect driving performance and visual distraction.

Spatial layout of touchscreen elements directly shapes driver attention and control. Lamble et al. [66] and Wittmann et al. [113] demonstrated that distraction grows exponentially as the distance between a driver's primary visual field and touchscreen interaction point increases. Wu et al. [116] further emphasized that homepage layout significantly affects mean glance time, glance count, lateral lane deviation, and speed variability, showing that even small changes in spatial arrangement can alter driving stability. Likewise, menu depth and breadth increase task completion time and visual demand [40, 75]. Menu traversal mechanics also influence glance duration variability, indicating that interface design modulates distraction [64, 65, 67].

Button size and density also affect visual attention. Increasing button quantity or reducing button size elevates visual demand, whereas larger and fewer buttons yield more efficient glance behavior [27, 63, 98]. These findings directly link spatial density and target size to distraction risk, highlighting the trade-off between information richness and safety. Complementary work on visual salience shows that arranging elements closely together can enhance search efficiency [87], but overly dense configurations may lead to crowding effects, reducing recognition of individual targets [105]. Moreover, Yoon et al. [118] observed that visual features such as icon dimensions, density, and color variability significantly affect perceived complexity and thus impact search efficiency. Beyond layout and density, physical touchscreen properties also influence driver attention. Ma et al. [76] and Brown et al. [10] found that larger screens led to significantly longer glances, but also fewer glances, thereby increasing long-glance risk without necessarily impairing steering wheel control.

Taken together, interface design characteristics systematically affect glance behavior, workload, and driving performance. However, most studies have focused on static design guidelines or isolated factors, which are difficult to translate into actionable, context-sensitive guidance on adapting to the dynamic driving demands.

2.3 Adaptive User Interfaces in Driving Contexts

Adaptive user interfaces have been designed and deployed across multiple domains, including desktop productivity software [21, 81, 90], mobile and small-screen interfaces [28], and pointing/target-selection tools [52], enabling systems to accommodate diverse users and contexts [1, 55]. Some adaptive interfaces have similarly been shown to improve task performance in driving contexts [68]. For example, Meiser et al. [82] proposed a workload-contingent automotive interface that adapts to environment-induced driver mental workload, and Lavie et al. [68] found that an in-vehicle telematics system reduced task completion time and lane deviation. *AdaptiveVoice* [111] adapts the brevity of voice interactions to support driving performance under high cognitive load. Other work reduces distraction by attenuating voice or visual information when hazards are detected [35, 102]. *CARSI II* [112] develops a context-aware recommender system for infotainment content, whereas *DriverSense* [59] reconfigures smartphone UIs during driving based on environmental context and driver preferences.

However, potential downsides of excessive or ill-timed adaptations remain underexplored. In unfamiliar situations, fully adaptive interfaces can *increase* cognitive workload and impair performance [68]. Designing and evaluating adaptive in-car systems therefore requires accounting for both benefits and risks. Designers could benefit from a generalizable framework linking adaptation policies and actionable UI design guidelines to cognitive load and driver characteristics, as well as computational models providing practical and usable predictions tied to interface design [74].

Classical computational models offer both foundations and a point of comparison. *Adaptive Control of Thought-Rational (ACT-R)* [4] offers a compact account of how drivers schedule visual and cognitive resources across primary and secondary tasks, while *Goals, Operations, Methods, and Selection Rules (GOMS)* [56] decomposes touchscreen workflows into primitive operators that estimate task time and associated eyes-off-road costs. The framework we develop in the following sections builds on *ACT-R* and *GOMS* (as well as their automotive follow-ups [89]). Our framework integrates empirical findings with expert knowledge and a predictive model to support design patterns that helps designers better account for the complex interplay between user preferences and real-time user state.

3 Phase 1 – Observation: The Target Size/Pagination Trade-Off under Varying Cognitive Load

To develop a framework for in-vehicle adaptive user interface design, we first observed driver behavior to identify factors influencing driver touch performance and interaction patterns. This section describes our *Observation* phase in which we conducted a driving simulator study where participants operated a touchscreen under varying levels of cognitive load to measure trade-offs between layouts that vary button size and number of icon pages. Across six experimental conditions, we measured the impact of cognitive load and touchscreen configurations on touch performance and driving-related behavior.

3.1 Experiment Design

We conducted the study in a driving simulator (see Section 3.1.1). Driving scenarios were implemented using Town 10 in the open-source *CARLA* simulator [20]. Participants drove along the route shown in Figure 2, a continuous circuit along the map's outer perimeter road, while keeping a constant speed of 30 mph and staying within their lane. The repeatable route and constant-speed instruction were chosen to minimize primary-task variability (e.g., speed, steering), so observed differences could be better attributed to manipulations of layout and cognitive-load, consistent with prior distraction-assessment research using simple, traffic-free, straight courses [6, 80, 96].

Along with the driving task, participants tapped designated buttons on a touchscreen, as shown in Figure 2. A *Samsung Galaxy Tab S9 FE* with a 10.9-inch display was mounted to the right of the simulator seat, and the in-vehicle touchscreen UI was simulated using the *Unity* game engine. This layout mirrored a typical in-vehicle touchscreen UI, with interactive buttons on the left two-thirds of the screen and a navigation map with the driving route on the right one-third (e.g., a typical arrangement in *Android Auto* systems [72]).

The experiment was conducted using a within-subjects design. Each participant experienced *three touchscreen layout conditions* and *two levels of cognitive load*, experiencing a total of *six experimental conditions*. The following sections describe: (1) how the three touchscreen layouts were designed and what tasks participants performed, and (2) how the two cognitive load conditions were designed and what tasks participants performed.

Touchscreen Layouts. Each touchscreen layout comprised 16 buttons organized into one of three configurations (Figure 2). Each configuration varied the number of buttons on a page and the number of pages across which buttons were placed. In the 4×4 layout condition, all 16 buttons were visible on a single page. In the 4×2 layout condition, the 16 buttons were split across two pages. In the 2×2 layout, the buttons were split across 4 pages. Participants could use a swipe gesture to access different pages. The buttons always occupied two-thirds of the touchscreen, such that buttons were larger for layout configurations with fewer buttons per page.

During the task, participants were instructed to find and tap buttons in each layout. Each button was labeled with a single letter and voice commands told participants which button to tap. Participants were instructed to respond as quickly and accurately as possible and completed trials until they had successfully tapped each button twice (i.e., 32 trials per condition). Correct taps caused buttons to light up blue and play a bell sound. Incorrect taps caused the button to turn red and play a beep sound. After each tap, the interface returned to the first page before the next trial. To prevent learning, button positions and sequences were randomized for each condition.

Cognitive Load. To manipulate cognitive load during driving and touchscreen tasks, participants were asked to perform the *Serial-7s* task [99], a widely-used method for inducing cognitive load. Participants started at 100, subtracted 7 at each step, and verbalized the resulting number aloud (e.g., 100, 93, 86, 79, ...). Participants were required to verbalize a number every three seconds to maintain consistent cognitive load over time and to prevent deliberate slowing to reduce load. We defined the low-load condition as the absence of the Serial-7s task and the high-load condition as the presence of the Serial-7s task.

3.1.1 *Simulation Implementation.*

We conducted the experiment using the *Town10* map of *CARLA*, an urban environment depicted in Figure 2. The simulator employed a *Fanatec Podium Wheel Base DD2* steering wheel and *Fanatec Clubsport Pedals V3*, both mounted on a frame with a *Sparco* racing seat. A 49-inch widescreen monitor was affixed to the simulator frame. Seat position, steering wheel height, and pedal distance were fully adjustable to individual preferences. Gaze behavior was captured using the *Pupil Labs NEON*, a head-mounted, video-based eye tracker with 1.8° accuracy that includes an accelerometer, magnetometer, and gyroscope to track head position and orientation.

3.1.2 *Perceived Workload.*

Workload was measured using the NASA-TLX questionnaire [46, 47]. Participants completed the questionnaire after each condition to report the perceived workload experienced while performing the task.

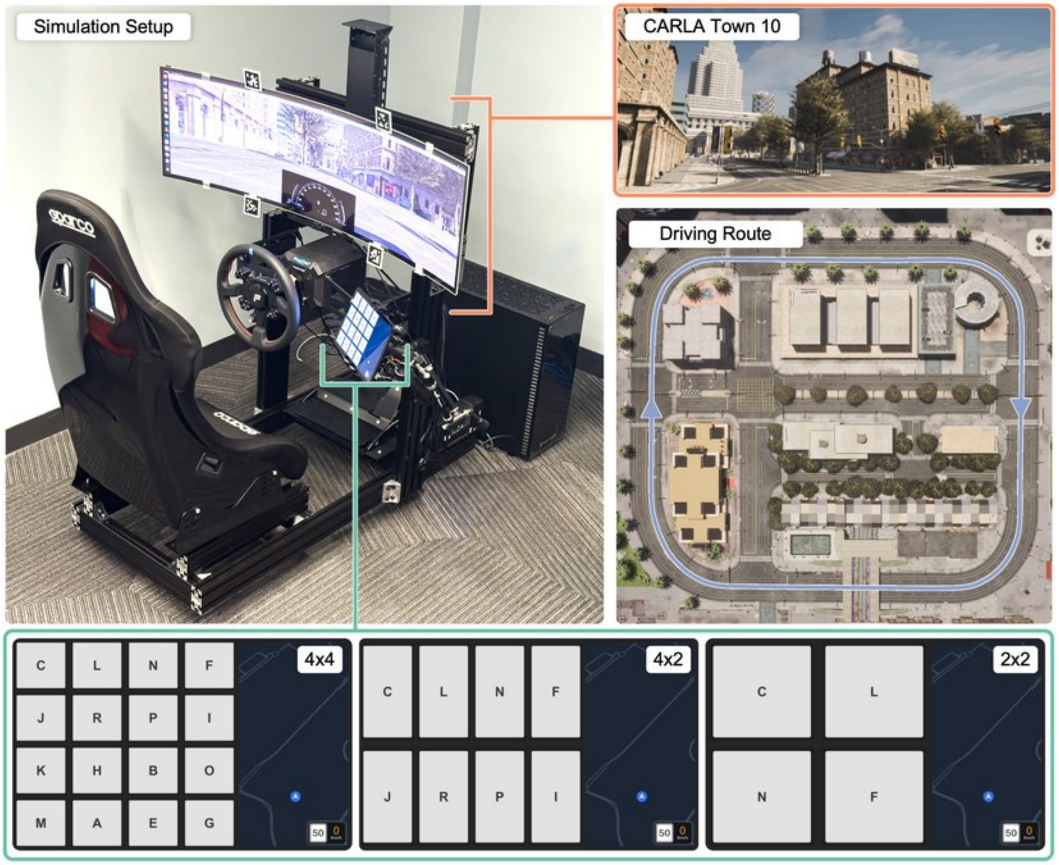


Figure 2: Experimental simulation environment consisting of a steering wheel, pedals, seat, and monitor, with CARLA and the adaptive UI simulation running on this platform.

3.1.3 *Driving Behavior.* Driving performance was analyzed using *lateral deviation variance* and *pedal variance*, both commonly used to assess driving performance [31, 48, 73, 98, 101, 103]. Lateral deviation variance was calculated as the variance of the distance between the center of the vehicle and the center of the lane, reflecting steering control. Pedal variance was calculated as the variance of normalized accelerator input (scaled $0-1$), reflecting speed control.

3.1.4 *Touchscreen Behavior.* Touchscreen performance was assessed by measuring selection time (i.e., between a voice instruction and a corresponding button tap). Voice instructions and touch events were recorded within the *Unity* game engine at a frame rate of 60 fps.

3.1.5 *Gaze Behavior.* Gaze patterns were measured using 2D gaze coordinates, inertial measurement unit (IMU) quaternions, and raw accelerometer channels available on the *Pupil Labs NEON* sensor [92]. Head orientation was estimated from IMU quaternions using the *Pupil Labs Library* [91]. Forward head direction was defined as the IMU-local y-axis rotated into world space to obtain a unit vector $\mathbf{f}$. From this, we formed an orthonormal basis for a head-oriented plane: $\mathbf{r} = \frac{\mathbf{f}\times\hat{\mathbf{z}}}{\|\mathbf{f}\times\hat{\mathbf{z}}\|}$ (falling back to $\hat{\mathbf{x}}$ if $\mathbf{f}$ is nearly collinear with $\hat{\mathbf{z}}$) and $\mathbf{u} = \frac{\mathbf{r}\times\mathbf{f}}{\|\mathbf{r}\times\mathbf{f}\|}$. The plane's width and height were set by the tracker's horizontal/vertical FOVs (103° and 77°, respectively). The settings yields a head-stabilized local screen for each sample that moves with the participant. Raw gaze arrived as pixel coordinates on a nominal 1600×1200 surface. For valid gaze sample data, we computed normalized coordinates and mapped them to the plane and projected into world coordinates. Thus, every valid time sample produced a head-referenced 3D gaze point. Using these 3D gaze coordinates, we derived two gaze metrics: *screen transitions* and *off-road gaze time percentage* [18, 94, 97, 98, 119]. screen transitions denote how many times the driver's gaze shifted between the road and the touchscreen. off-road gaze time percentage denotes the proportion of total time the driver was not looking at the road. All data were cleaned by removing outliers beyond ±2 standard deviations.

3.1.6 *Participants.* Twelve participants (mean age = 39.5, *SD* = 15.4; 7 men, 5 women) were recruited. All were aged 18 or older with a valid driver's license and were not wearing glasses to ensure eye-tracking accuracy. Exclusion criteria included pregnant individuals, individuals with pacemakers, those with sensitive skin, and those highly susceptible to motion sickness in 3D simulation environments. Participants received $120, and the total duration of the experiment was 90 minutes. All procedures were approved by our organization's Institutional Review Board and all participants provided informed consent.

3.1.7 Procedure. After adjusting their seating position, participants completed a minimum five-minute *driving practice session* to become familiar with the simulator and the route. During this practice, they were instructed to maintain a steady speed consistent with their usual driving habits while prioritizing safe driving. Participants next completed a *touchscreen task practice session*. Following spoken instructions, they tapped the indicated buttons until all 16 buttons had been tapped at least twice. Finally, participants received instructions for the Serial-7 task and completed a minimum three-minute practice session. Additional practice time for any of these tasks was provided upon request to ensure participants were comfortable before the experiment began.

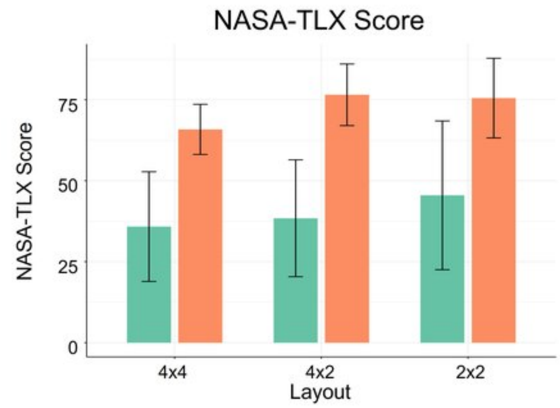
After two practice sessions, participants put on the eye-tracker and completed the six experimental conditions. The six conditions (three touchscreen layouts × two levels of cognitive load) were ordered using a balanced Latin Square. Across participants, each condition appeared equally often in each serial position and preceded every other condition an equal number of times.

At the beginning of each condition, participants were instructed to drive at a constant speed of 30 mph within the designated route while prioritizing safe and steady driving over the secondary tasks (i.e., the touchscreen task and, when applicable, the Serial-7 task). When the vehicle first reached 30 mph, participants began the touchscreen task and the Serial-7 task (i.e., according to the assigned condition). After all 16 buttons had been tapped twice, participants stopped the vehicle and completed the NASA-TLX [46, 47] on the tablet. A rest period of at least five minutes was provided before the next condition, with additional rest upon request.

3.2 Results: Quantitative Findings

3.2.1 Driver Cognitive Load. We first verified that the Serial-7s task successfully increased participant perceived mental workload (Figure 3). Participant NASA-TLX scores were higher in conditions where participants performed the Serial-7s task in addition to the touchscreen task (using an analysis of variance based on the aligned rank transform [50, 51, 79, 114]: ($F(1, 50.19) = 170.38$, $p < .001$). Moreover, touchscreen layout did not influence NASA-TLX ratings ($F(2, 50.37) = 3.12$, $p = .053$) and there was no cognitive load by layout interaction ($F(2, 50.19) = 0.33, p = .719$). These results indicate that our manipulation successfully increased cognitive load whereas load did not vary as a function of touchscreen layout.

3.2.2 Driving Performance. We next examined the influence of cognitive load on driving performance (Figure 4). Overall, cognitive load did not have an influence on our measured driving metrics (gamma GLMM for lateral deviation [26]: $\chi^2(1, N = 59) = 1.98$, $p = .159$; pedal variance: $\chi^2(1, N = 59) = 0.18$, $p = .671$). Additionally, touchscreen layout did not influence driving metrics (lateral deviation: $\chi^2(2, N = 59) = 0.59$, $p = .743$; pedal variance: $\chi^2(2, N = 59) = 4.64$, $p = .098$) nor did we observe any cognitive load by layout interactions (lateral deviation: $\chi^2(2, N = 59) = 5.01$, $p = .082$; pedal variance: $\chi^2(2, N = 59) = 2.02$, $p = .364$). As such, driving performance was consistent across conditions, suggesting



		4x4	4x2	2x2
w/o Serial-7	*M*	35.8	38.4	45.5
	SD	16.9	18.0	23.0
w/ Serial-7	*M*	65.8	76.5	75.5
	SD	7.7	9.51	12.3

Figure 3: Participants' NASA–TLX scores by layout and by presence/absence of the Serial-7 task; error bars indicate standard deviations.

that drivers followed our instructions to prioritize driving performance and safety over secondary tasks (i.e., touchscreen presses and Serial-7s).

3.2.3 Touch Selection Time. An analysis of variance using mixed gamma regression with random intercepts for participant indicated a statistically significant effect of cognitive load on selection time ($\chi^2(1, N = 70) = 25.49$, $p < .001$), and the effect of layout was also statistically significant ($\chi^2(2, N = 70) = 120.66$, $p < .001$). The *Layout* × *Load* interaction was not statistically significant ($\chi^2(2, N = 70) = 3.61$, $p = .165$).

Figure 5 illustrates selection time by button index for each layout, with dashed horizontal lines representing the average selection time for buttons on the same page. As shown, selection time increased in a stepwise manner across pages. Furthermore, higher cognitive load increased selection time across all layouts, button indices, and pages, indicating that cognitive load impaired visual search and button selection.

Figure 6 also compares selection times across layouts for each cognitive load level. On the first page, layouts with fewer and larger buttons yielded shorter selection times, with the 2×2 layout being the fastest and the 4×4 layout the slowest. Moreover, on the second page of the 4×2 and 2×2 layouts, the 2×2 layout consistently showed faster selection times than the 4×2 layout.

To further quantify these effects, for each layout × cognitive load × page condition we applied robust LOESS regression [15] across button indices, fitting within each page to avoid cross-page smoothing. We then obtained the predicted selection time for each index and computed page-level averages as attempt-weighted means of those predictions (Table 1). The results showed that higher cognitive load increased selection time by 0.34 s in the 4×4 layout, 0.38 s in the 4×2 layout, and 0.45 s in the 2×2 layout. On the first page under low load, the 2×2 layout was faster by 0.11 s compared to

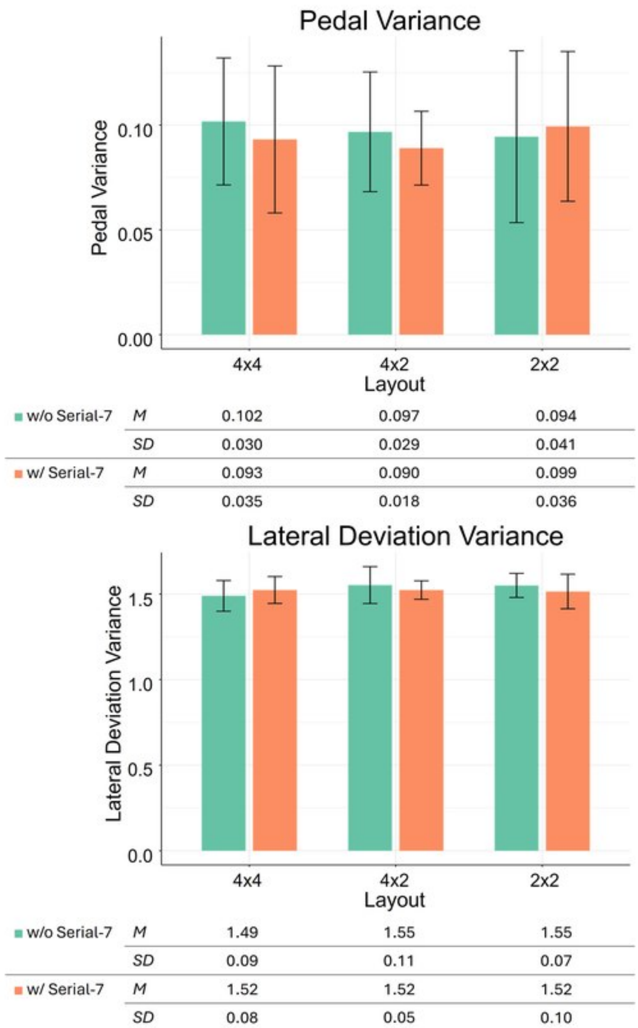


Figure 4: Participants' driving performance–pedal variance and lateral deviation variance–by layout and by presence/absence of the Serial-7 task; error bars indicate standard deviations.

4×2 and 0.35 s compared to 4×4; under high load, it was faster by 0.04 s and 0.37 s. On the second page, 2×2 was faster than 4×2 by 0.19 s (low load) and 0.17 s (high load).

Within layouts, page progression had a pronounced effect. In the 4×2 layout, selection time increased by 1.05 s (low load) and 1.30 s (high load) from page 1 to page 2. In the 2×2 layout, page increases yielded 0.96 s (low load) and 1.16 s (high load) from page 1 to page 2, 0.92 s (low load) and 0.80 s (high load) from page 2 to page 3, and 1.02 s (low load) and 1.16 s (high load) from page 3 to page 4.

In summary, cognitive load generally increased selection time. Within a single page, fewer and larger buttons reduced selection time, but within the same layout, selection time substantially increased as the number of pages increased.

Table 1: Differences in expected selection time by condition, computed using robust LOESS regression [15]. Baselines: (1) Load effect uses Low as baseline; (2) Layout differences use 2×2 as baseline on the same page and load; (3) Page progression uses the immediately previous page as baseline within the same layout and load. Positive Δ indicates slower selection time; negative indicates faster.

Condition-wise deltas (absolute & relative).

Load	Layout	Page(s)	Δ (ms)	Δ (%)
(1) Load effect within layout				
High vs. Low	4×4	All pages	+343	20.2%
High vs. Low	4×2	All pages	+375	18.8%
High vs. Low	2×2	All pages	+450	16.2%
(2) Layout differences on Page 1 (per load)				
Low	4×2 vs. 2×2	p1	+106	7.9%
Low	4×4 vs. 2×2	p1	+351	26.2%
High	4×2 vs. 2×2	p1	+35	2.1%
High	4×4 vs. 2×2	p1	+373	22.5%
Layout differences on Page 2 (per load)				
Low	4×2 vs. 2×2	p2	+194	8.4%
High	4×2 vs. 2×2	p2	+172	6.1%
(3) Page progression within layout (later page vs. previous)				
Low	4×2	p2 vs. p1	+1050	72.4%
High	4×2	p2 vs. p1	+1300	76.5%
Low	2×2	p2 vs. p1	+960	71.6%
Low	2×2	p3 vs. p2	+920	40.0%
Low	2×2	p4 vs. p3	+1020	31.7%
High	2×2	p2 vs. p1	+1160	69.9%
High	2×2	p3 vs. p2	+800	28.4%
High	2×2	p4 vs. p3	+1160	31.9%

3.2.4 Driver Gaze Analysis. An analysis of variance based on the aligned rank transform indicated a statistically significant effect of cognitive load on the number of screen transitions, $F(1, 47.24) = 22.44$, $p < .001$, a significant effect of Layout, $F(2, 47.60) = 60.24$, $p < .001$, and a non-significant interaction effect, $F(2, 47.36) = 1.61$, $p = .210$. For the percentage of off-road glance time, a gamma GLMM analysis revealed that the effect of cognitive load was not significant, $\chi^2(1, N = 69) = 1.47$, $p = .225$, the effect of layout was not significant, $\chi^2(2, N = 69) = 4.20$, $p = .123$, and the interaction effect was not significant, $\chi^2(2, N = 69) = 2.01$, $p = .367$. These results indicate that, although total off-road glance time did not differ significantly, drivers looked at the screen more frequently under higher cognitive load and in layouts with fewer buttons per page (i.e., more pages). This combination implies more frequent but shorter glances to the touchscreen.

We further plotted transition counts by button index for conditions showing statistically significant differences in cognitive load and layout (Figure 7). We found that layouts with fewer, larger buttons elicited shorter but more frequent gaze shifts, and that the frequency of gaze transitions increased proportionally with the number of pages. In summary, higher cognitive load and layouts with more pages led drivers to make more frequent and shorter gaze shifts, with buttons located on later pages requiring more transitions.

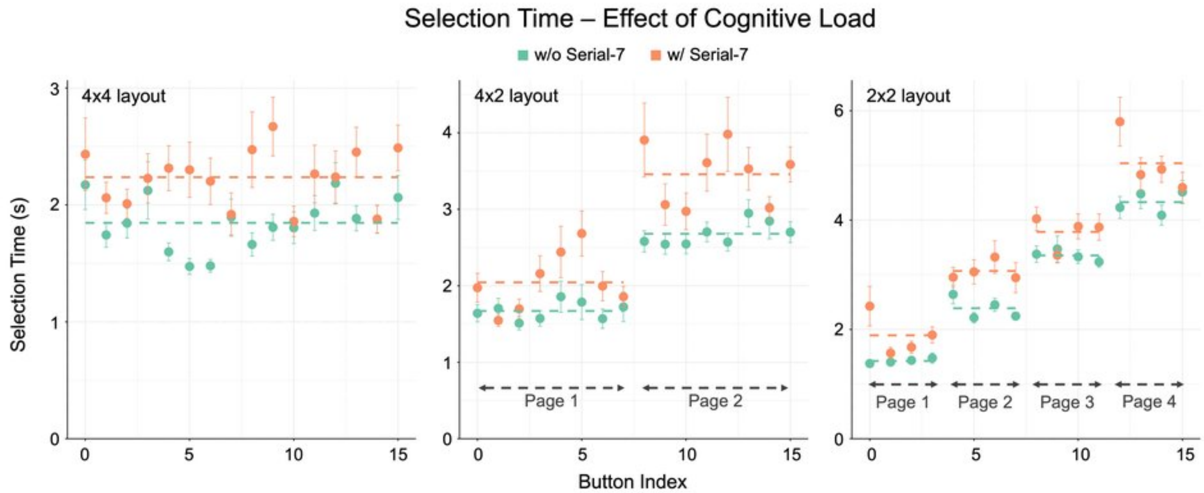


Figure 5: Participants' selection times by layout and button index. Data points include error bars indicating ±1 standard deviation; page-level means are shown as horizontal dashed lines.

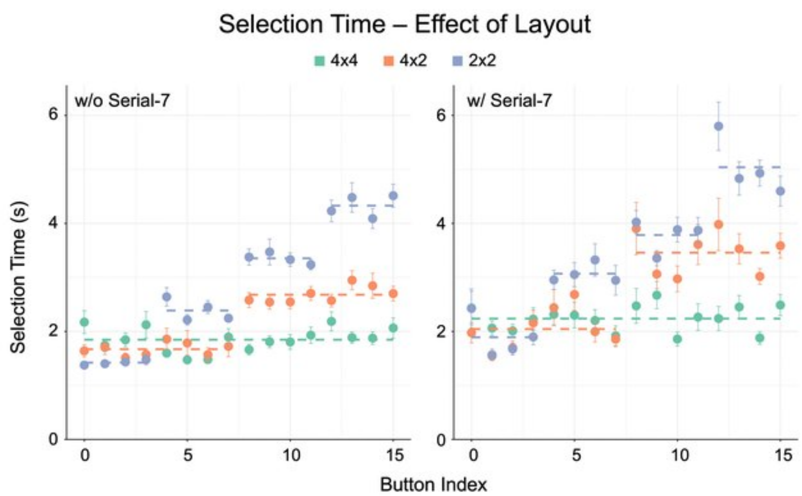


Figure 6: Participants' selection times by presence/absence of the Serial-7 task and by button index. Data points include error bars indicating ±1 standard deviation; page-level means are shown as horizontal dashed lines.

3.3 Results: Qualitative Findings

Although Phase 1 was designed primarily as a controlled experiment, we also conducted brief informal interviews to understand how participants experienced the different combinations of layout and cognitive load. After each block and at the end of the session, the first author asked each participant open-ended questions about their overall experience with the tasks, the simulator, and the touchscreen interactions. We clustered participant reactions into recurring themes, which are summarized in Table 2 with participant identifiers P_o^1–P_o^{12}. These themes align with the quantitative patterns in NASA–TLX, touch selection time, gaze transition counts, and off-road glance time.

Mental Workload and Task Prioritization. Participants consistently described the Serial-7s task as overwhelmingly demanding, saying that counting backwards "took all of my attention" (P_o^4) and felt stressful. Several noted that, under high cognitive load, they deliberately prioritized lane keeping and the counting task, postponing or abandoning touchscreen interactions when the numbers became difficult. These observations align with the quantitative pattern in which the Serial-7s task substantially increased NASA-TLX scores and touch selection time, while lateral deviation variance and pedal variance remained relatively stable (Figures 3 and 4). The results indicate that participants managed limited attentional resources by preserving basic driving control at the cost of slower

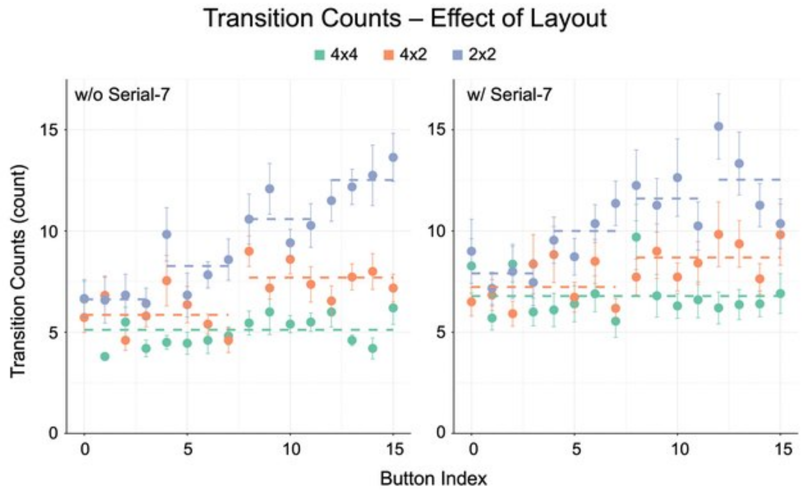


Figure 7: Participants' number of screen transitions by presence/absence of the Serial-7 task and by button index. Data points include error bars indicating ±1 standard deviation; page-level means are shown as horizontal dashed lines.

Table 2: Summary of recurring themes from informal participant interviews in Phase 1.

Theme	Representative comments
Mental workload and task prioritization	Counting backwards was terrible; it took all of my attention and felt stressful. – P_o^4 When I tried to do the math and move my hand to the screen, I either lost the number or turned to the wrong page. – P_o^4 Driving and using the touchscreen alone was fine, but with counting I pushed the touchscreen task to the back of the queue. – P_o^9
Dense layouts and small targets	When there were many buttons on one page, it felt crowded and I needed more time to find the right one. – P_o^2 Sometimes I was sure I hit the right button, but the one next to it was activated. – P_o^2 Small buttons were annoying while steering; I had to be very careful with my finger. – P_o^{12}
Multi-page navigation and place-keeping	With many pages I sometimes forgot which page I was on. – P_o^1 I reached the last page and still could not find my button, then realized I must have missed it on an earlier page. – P_o^1 Turning pages was frustrating; every new page felt like starting the search from the top again. – P_o^6 I sometimes flipped the page by accident when I meant to press a button near the edge, and sometimes the other way around. – P_o^{10}
Gaze behavior under load	I did not want to look away for too long, so I broke it into short glances and sometimes forgot how far I had read. – P_o^3 With multiple pages I kept going back and forth between the road and the screen. – P_o^7

touchscreen selections, consistent with the main effect of cognitive load on selection time in Section 3.2.3.

Layout Density, Small Targets, and Selection Errors. Participants also reacted strongly to the spatial density of buttons. Layouts with many small buttons on a page were described as "felt crowded" and "needed more time to find" (P_o^2), with several participants reporting that "small buttons were annoying while steering" (P_o^{12}) and that adjacent buttons were sometimes activated instead of the intended one. These perceptions align with the robust main effect of layout on selection time (Section 3.2.3): layouts that packed more buttons into a single page yielded systematically slower and more variable selections than layouts with fewer, larger buttons. Mistaps and cautious finger movements provide a plausible subjective mechanism for the additional time costs observed for dense layouts beyond what is explained by visual search alone.

Multi-Page Navigation, Place-Keeping, and Gaze Behavior. Multi-page navigation introduced a distinct form of difficulty. Participants described page turns as "frustrating" (P_o^6), reporting that each new page required re-scanning from the top, that they sometimes lost track of which pages they had already checked, and that they occasionally reached the last page without finding the desired button. Some also mentioned accidental selections, including page flips when aiming for buttons near the edge and unintended button selections while trying to advance the page. These reports are consistent with the stepwise increase in selection time across pages within the same layout (Figure 6, Table 1). Participants further explained that layouts with multiple pages, especially under high load, made them "keep going back and forth" (P_o^7) between the road and the screen and encouraged them to break their interaction into many short glances rather than a few long ones. Such behavior helps interpret our gaze results (Section 3.2.4): layouts with more pages and higher load increased the number of screen transitions (Figure 7), while the overall percentage of off-road glance time remained relatively unchanged, suggesting that drivers fragmented a similar off-road time budget into a greater number of shorter glances.

4 Phase 2 – Co-Design: Designing an Adaptive UI Framework from Driver Behavior Observations

Building on the quantitative results from the *Observation* phase, this phase aimed to: (1) interpret observed driver behavior, (2) consolidate design concerns for driving safety, and (3) translate these concerns into an adaptive UI framework through co-design sessions with in-vehicle UI experts. We therefore designed a single two-hour workshop structured in four sequential stages: *Onboarding*, *Observation Briefing*, *Open Guideline Discussion*, and *Adaptive Policy & Design Sketches* (Figure 8).

Although co-design research often employs multiple iterative workshops to refine ideas and design sketches [42], our participants were senior in-vehicle HMI (Human–Machine Interface) designers with demanding professional schedules, and organizing a series of workshops would have restricted their participation. Consistent with prior work that treats co-design workshops as time-constrained events that must fit within the limited availability of stakeholders, we adopted a single session format. Naranjo-Bock's [84] overview of creativity-based co-design describes co-design workshops as time-bounded sessions (typically 1.5-2 hours) that enable collaboration in knowledge development and idea generation. Miller et al. [83] similarly characterize rapid co-design and design-thinking sprints as "time-constrained creative" events, reporting that such sprints can range from a few hours to a day or a week, and describing cases in which even 1-hour co-design sprints with busy clinicians produced high-quality concepts that teams further refined and implemented. Our single-session design reflects a trade-off between depth and feasibility, consistent with prior recommendations for short, well-facilitated co-design events. Nonetheless, because co-design outcomes often benefit from repeated cycles of iteration and reflection, our single-session approach may have limited the depth of critique and the evolution of ideas; future studies should examine how multi-session formats further develop and validate the generated concepts.

4.1 Co-Design Method

4.1.1 Participants. Four professional UI/UX designers specializing in automotive HMI, mobile UI, and interaction design participated (Table 3), with participant identifiers P_c^1–P_c^4. Their average industry experience was 17.75 years, and they were selected primarily for their prior experience designing either commercial products or concept systems in safety-critical or automotive domains. Sessions were conducted online and lasted two hours. Participants were compensated $200 total. All procedures were approved by our organization's Institutional Review Board and all participants provided informed consent.

4.1.2 Procedure. As depicted in Figure 8, each co-design session followed four processes:

- **Onboarding:** The facilitator stated the session goals and framed the problem of implementing an adaptive user interface for driver safety. Consent was obtained, and participants were oriented to the shared working surface used during the session. We began recording and asked about participant professional backgrounds and experience with automotive design.
- **Observation Briefing:** The facilitator presented key results from the *Observation* phase, including selection-time patterns by layout and page, the cost of page switching, and search delays under higher cognitive load. Screenshots of example layouts were also provided. Participants could ask clarification questions at any time during the briefing, and an additional Q&A session followed to ensure shared understanding. Supplementary statistics were provided upon request, and presentation materials remained accessible throughout subsequent phases. The briefing lasted approximately 20 minutes.
- **Open Guideline Discussion:** Designers proposed heuristics for safer touchscreen interaction during driving, unconstrained by implementation feasibility. Following the open discussion, the facilitator provided prompts (e.g., *"minimize transitions", "preserve predictability"*) to synthesize the ideas and deliberations and to balance divergent and convergent thinking. This discussion lasted 50 minutes.
- **Adaptive Policy & Design Sketches:** Participants refined the heuristics derived from the open discussion into specific adaptation targets (i.e., *what* to adapt). Finally, they articulated policy statements specifying *when* to trigger adaptation, *what* to change, and *how* to preserve interface stability. The facilitator iteratively refined these statements through live sketches. This phase lasted 50 minutes.

4.1.3 Data Analysis. We analyzed the co-design session transcripts using thematic analysis [8]. During the co-design sessions, three authors independently took field notes to record key points raised during discussions. After all co-design sessions were completed, verbatim transcripts were generated using automatic transcription software. The same three authors each used the transcripts and recordings to manually code segments they judged relevant to our design elements and problem scenarios, extracting key statements and observations. Building on the transcripts, recordings, and notes, the first author conducted a holistic review of the full corpus and synthesized the independently produced codes into three preliminary themes. These candidate themes were subsequently discussed in a consensus meeting among the three authors who participated in the co-design sessions. The authors refined theme boundaries, agreed on shared labels, and confirmed representative keywords

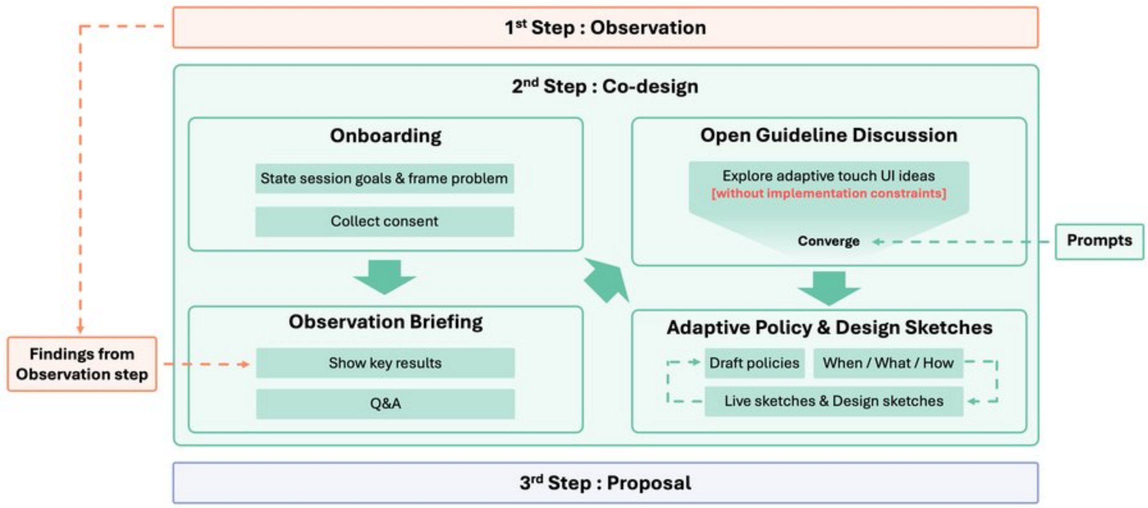


Figure 8: Process flow diagram for the second phase: Co-design.

Table 3: Profiles of co-design participants (P_c): roles, organization types, experience, and primary domains.

PID	Role / Discipline	Org. Type	Years	Primary Domain
P_c^1	Industrial Designer	Automotive design	15	In-cabin UX/UI; concept layout
P_c^2	UX / Interaction Designer	Automotive UX (R&D)	26	AR HUD; In-vehicle infotainment systems
P_c^3	UX Designer	Automotive UX (R&D)	10	In-vehicle infotainment systems / on-road widget systems
P_c^4	Automotive HMI Designer	Vehicle OEM	20	HMI; HUI/HUD; interior prototyping

and excerpts. Finally, using the finalized set of three themes as the organizing scheme, the first author classified designer-proposed design sketches by their dominant thematic emphases. As a result, we identified three design concerns, which served as the basis for an adaptive user interface framework with multiple design patterns.

4.2 Results: Design Concerns

Outputs of the co-design sessions were refined around recurring rationales across transcripts and artifacts, resulting in three core design concerns.

The Adaptability-Stability trade-off: When to make structural changes versus only cosmetic adjustments?

> *"Adapt, yes, but the spatial backbone should stay fixed ... Drivers rely on spatial and muscle memory, and moving targets during driving erodes predictability and trust." –* P_c^1

> *"Continuous, under-the-hood layout changes are distracting ... Real-time adaptation should adjust salience, size, contrast, highlights, [but] not move targets." –* P_c^1

> *"Show minimal controls while driving ... reveal the full suite only when appropriate. Don't surface deep structure in high-load moments" –* P_c^3

First, the principle of a *Adaptability-Stability trade-off* emerged as both the starting point and governing rule. Designers emphasized that a driver's accumulated spatial and muscle memory of touchscreen layouts is crucial to predictability and trust. High-adaptation strategies, such as altering grids, page counts, button order, or relative positions, can yield substantial performance gains that might seem ideal for isolated touch events, but they can also impose high relearning costs and uncertainty. In particular, changes to paging structures or primary-area reassignments, when combined with the page-transition delays observed in the *Observation* phase, may lead to both slower interaction times and diminished UI predictability. Designers pointed to the stepwise page-depth penalties quantified in Section 3.2.3: in the 2×2 layout, LOESS means indicated that targets on pages 2 – 4 were approximately 1.0, 1.7, and 3.0 s slower to select than targets on page 1, and even the 4×2 layout incurred an additional 0.4 – 0.5 s on page 2 relative to page 1 (Figure 6, Table 1). When combined with the 0.4 – 0.5 s slowdown induced by high cognitive load alone across layouts (Figure 5, Table 1), designers argued that any real-time structural adaptation that moves a frequently used function from an early page to a deeper one during driving would stack layout-induced page-depth costs on top of load-induced slowdowns, while simultaneously invalidating the driver's learned spatial and proprioceptive map of the interface.

Conversely, surface-level cosmetic adaptations that adjust attributes such as size, color, contrast, brightness, or font were regarded as more appropriate for real-time adaptation, as they alter perceptual weight without disturbing the underlying spatial frame. Designers made this distinction concrete by treating *large* changes as those that alter page structure or reassign functions across the

4×4, 4×2, and 2×2 layouts (e.g., moving a control from page 1 to page 3), and *small* changes as those that preserve grid and page order while scaling or highlighting targets without relocation (e.g., temporarily enlarging or brightening the most probable buttons on the current page). Additionally, a consensus was reached on deliberately separating adaptation across temporal scales: only low-level cosmetic adaptations should occur during driving, whereas high-level structural adaptations should be bundled into long-term change windows (e.g., onboarding, software updates, scheduled updates) where drivers receive advance notice, confirmation steps, and options to revert. Such change windows should include previews highlighting before-and-after differences, lightweight tutorials on first entry, and grace periods for reverting. Crucially, real-time adaptation must never cause target relocation or reflow. Designers further recommended applying hysteresis to cosmetic adaptations so that brief threshold fluctuations do not cause flickering or oscillation in the interface.

The Profile-State axis: Balancing long-term priorities against short-term cognitive bandwidth.

> *"Different drivers want different things. Some need sport controls instantly, others never touch them ... Let long-term usage learn priorities and keep those up front." –* P_c^1
>
> *"Under high cognitive load, go flatter and simpler ... make fewer, clearer choices and bigger, more findable targets." –* P_c^3
>
> *"Prioritize by likelihood of selection. Make probable actions easier and more visible." –* P_c^4

Second, participant responses converged on a conceptual *Profile-State axis* formalized to organize adaptation decisions. A driver's profile reflects long-term preferences and usage patterns, determining how UI functions and features should be grouped and arranged. Privacy and explainability in profile learning were emphasized as requirements on par with safety, with cold-start phases defaulting to robust universal priorities (e.g., navigation, calls, media control) and minimal-page layouts, before allowing periodic opportunities to propose layout adaptations as usage patterns stabilize. Designers linked this long-term profiling to the layout-level selection-time differences observed in the *Observation* phase: under low cognitive load, mean selection times were approximately 2.44, 2.07, and 1.92 s for the 4×4, 4×2, and 2×2 layouts, respectively; under high load, they increased to 2.89, 2.49, and 2.34 s (Figure 6). They argued that profile-driven layout choices should therefore keep a driver's most frequent actions on earlier pages in the more efficient layouts, using long-term usage statistics to minimize the expected selection time for that driver.

By contrast, a driver's state reflects short-term variability in cognitive bandwidth, directly linked to the observed increase in search and decision costs under high cognitive load. In our data, adding the Serial-7s task significantly increased NASA-TLX workload scores across all layouts (Figure 3; ($F(1, 50.19) = 170.38$, $p < .001$) and slowed touch selections by roughly $0.4 - 0.5$ s on average (Figure 6). Designers interpreted this pattern as indicating that, under high cognitive load, drivers largely preserve steering and speed control but have less residual capacity for visual search and decision-making on the touchscreen. Adaptations along this axis are regarded as requiring temporary reweighting of visibility and accessibility, without structural changes: key functions should be selectively emphasized, non-essential ones visually de-emphasized but still legible, and notifications deferred into a "later" stack. This interpretation is reinforced by our gaze results: high-load conditions and layouts with more pages increased the number of road–screen gaze transitions, yet the overall percentage of off-road gaze time remained relatively stable (Figure 7). Designers took this as evidence that drivers maintain a roughly fixed "off-road time budget," fragmenting it into more shorter glances under demanding conditions, motivating state-based adaptations that reduce the number of viable on-screen choices and make the most relevant ones easily findable within each brief glance. Designers also emphasized that buffer zones around thresholds and rules to avoid overlap with driving events (e.g., acceleration, curves, lane changes) should be implemented to prevent new interface changes from coinciding with driving maneuvers.

A cross-cutting requirement: Minimize touch and gaze demands while maintaining predictability.

> *"Why do they have to touch anything? And only make them touch something if they have to." –* P_c^2
>
> *"Favor tactile and auditory confirmations—single, consistent gestures and haptics mean you don't have to verify with your eyes." –* P_c^2
>
> *"Provide peripheral cues and stable placement so targets are detectable before foveal attention arrives. Anchors speed re-orientation" –* P_c^3

Third, *minimizing touch and gaze demand* was identified as a cross-cutting requirement. Designers conceptualized interaction costs as a sequence of transitions—road to screen, within-screen search, and screen back to road—and emphasized reducing costs at each stage. This decomposition was grounded in the *Observation* phase gaze data: layouts with more pages and high cognitive load produced significantly more road–screen transitions, yet the overall off-road gaze-time percentage remained approximately constant across conditions (Figure 7). Designers interpreted each additional transition as a repeated "entry fee" for leaving and re-entering the roadway view, arguing that mitigation strategies should aim to reduce both the number of glances required to complete a task and the search effort within each glance. Core operations (home, back, volume) should always be accessible through fixed gestures or stable positions, supported by consistent tactile and auditory feedback to confirm that an action has been completed.

Proprioceptive anchors should be embedded within pages to help drivers quickly recalibrate hand position, while subtle salience cues (e.g., edge beacons, low-frequency highlights) should make targets discoverable even during brief glances. In the workshop artifacts, designers instantiated "proprioceptive anchors" as spatially and haptically stable reference points, such as a fixed vertical strip of core controls aligned with the driver's resting hand position, textured or raised edges that map to on-screen quadrants, and reserved corner regions for home and back actions. These anchors are intended to let drivers re-establish hand position and infer target locations using peripheral vision and touch, so that successive glances can jump directly to a narrow region instead of restarting a full-screen scan. This proposal directly responds to the page-depth penalties observed in the 2×2 layout, where later-page selections were up to 3 s slower than first-page selections (Table 1), and to the high transition counts observed for multi-page layouts under load (Figure 7). Such measures not only reduce time-to-target but also shorten recovery delays after errors. Designers agreed that multimodal inputs (e.g., voice, steering wheel buttons) should serve as fallback pathways rather than primary alternatives, with consistent feedback across modalities. They positioned these fallbacks as safety valves for the worst-case scenarios, such as repeated mistaps near page edges or overshooting the desired page in the 2×2 layout. For example, several concepts mapped “cancel” or “repeat last command” to steering-wheel buttons or short voice commands, allowing drivers to recover from an error or re-issue a command without incurring yet another costly road–screen–road round-trip.

4.3 The Profile-State Adaptive (PSA) Framework

Building on these co-design insights, we formalize policies organized by temporal scale and intervention strength. These policies form the backbone of our Profile-State Adaptive (PSA) framework. The guiding idea is to handle long-term, *profile*-based priorities and short-term, *state*-based attention demands with distinct rhythms of adaptation, while still preserving spatial predictability when both dimensions interact. Long-term profile adaptation follows permissive rules that allow higher-level structural changes. In contrast, short-term state adaptation follows conservative rules that restrict changes to low-level cosmetic properties. Across both axes, cross-cutting mechanisms operate continuously to reduce touch and gaze demand.

Profile-based long-term adaptation policy: Layout optimization based on the probability of selection. Profile-based long-term adaptation assumes that function priorities stabilize over time. Drawing on findings from our *Observation* phase, structural adaptations should project button-selection probability distributions (estimated from logs) onto layouts optimized to minimize expected selection time, accounting for page-transition costs and target-size benefits. Updates occur only during long-term change windows and must include previews, explanations, and options to confirm, postpone, or revert. Core anchors (e.g., home, back, volume, navigation entry) are protected from relocation. Each update limits both relocation distance and number of changes to preserve spatial memory, while respecting safety margins for target size and spacing per Fitts’ law [29, 98]. Thus, profile-based adaptation allows structural changes but constrains their timing, scope, and reversibility to preserve predictability.

State-based real-time adaptation policy: Focused cosmetic salience adjustments under a fixed layout. By contrast, state-based short-term adaptation modifies only cosmetic attributes while maintaining layout stability. Triggers are activated when cognitive load metrics exceed thresholds, with cool-downs to prevent rapid oscillation. Upon activation, the interface enters a *focus-mode* that subtly increases the salience of high-priority targets (through e.g., gradient rings, mild enlargement), reduces contrast of non-essential elements without impairing readability, and defers low-urgency notifications into a later stack for batch processing once load subsides. All changes occur as subtle animations, avoiding relocation or reflow. Temporal alignment rules delay or buffer such changes during dynamic driving events to prevent perceptual clutter. Exit from *focus-mode* occurs only after sustained sub-threshold stability, with gradual fade-outs rather than abrupt changes. Thus, real-time adaptations converged on three categories: (1) *Focused emphasis*, using mild highlights or enlargement to make top functions detectable in peripheral vision without intrusive pop-ups; (2) *Background attenuation*, reducing saturation and contrast of non-essential elements while maintaining text readability; and (3) *Notification deferral*, suppressing visual noise by redirecting notifications to a “later” stack for batch review during low cognitive load.

Common mitigation mechanisms: Persistent availability of global functions and haptic/visual anchors. On top of the two policy axes, a cross-cutting mechanism for *reducing touch and gaze demand* operates in all cases. *Global functions* such as home, volume control, and back must always be accessible through consistent buttons, voice commands, or gestures, redundantly mapped to steering wheel buttons or fixed sidebars so that one pathway immediately substitutes if another is unavailable. Gestures should be completed in a single step and confirmed with subtle haptic or auditory feedback, eliminating the need for drivers to visually verify completion. To support rapid spatial orientation of the hand, haptic cues can be provided on the screen bezel or steering wheel, intuitively indicating left, right, upper, and lower quadrants; in environments without proximity sensors, wheel-based tactile signals can serve as substitutes. Stable visual anchors should also be maintained across pages to provide consistent reference points for reconstructing hand-target coordinates, while subtle highlights or edge beacons detectable in peripheral vision should indicate the presence and boundaries of targets. These measures serve not only to reduce the time required for a single selection but also to clarify retry pathways after errors, shortening delays associated with failed attempts.

5 Phase 3 – Proposal: Practical Applications of Guidelines Derived from Co-Design

This section proposes the procedural and computational components required to translate the Profile-State Adaptive (PSA) framework policies into actual system designs. The core objective is to map the *Profile-State* axis to different time scales and interventions, enabling structural long-term adaptation to reflect each driver’s functional priorities, while supporting surface-level short-term adaptation to respond to fluctuations in cognitive bandwidth. To achieve this, we first introduce a *Time-Cost* layout model to automate profile-based long-term adaptation, and then propose *design patterns* for state-based real-time cosmetic adaptations for a stable interface layout.

5.1 Time-Cost Model for Profile-Based Long-term Adaptation

We introduce a *Time-Cost* model to recommend optimal layouts tailored to driver profiles. Profiles are operationalized as distributions of selection probability over buttons, reflecting difference in the selection patterns between drivers. In this section, we leverage selection time data collected in the *Observation* phase, measured by layout and button index, to implement the model and compute a *Time-Cost* across the three candidate layouts (4×4, 4×2, 2×2) for a given driver profile.

5.1.1 Building the Time-Cost Model and Input Validation. Formally, we define the *Time–Cost* (T_c) as in Equation 1. In this formulation, the overall cost of a layout is computed as the sum of per-outcome costs weighted by their occurrence probabilities, following the same principle as expected-utility models in decision theory and expected-cost models in HCI and interface optimization [3, 33, 106]. Expected value–based formulations have been used to evaluate menu hierarchies by combining the predicted time to reach each item with its selection probability [3], and to select personalized user interfaces that minimize the expected interaction cost for a given user profile [33].

For layout L, let the expected selection time of button index i be $T_i^{(L)}$, and let the probability that button i is requested for a given driver profile be P_i. The expected *Time-Cost* T_c of layout L and driver profile $\mathbf{P}$ is:

$$T_c(L \mid \mathbf{P}) = \sum_{i=0}^{n-1} T_i^{(L)} P_i. \tag{1}$$

Here, $T_i^{(L)}$ is derived from the fitted selection time data (e.g., robust LOESS regression curves by index and page), capturing both page transition costs and target size effects. $\mathbf{P} = \{P_0, \ldots, P_{n-1}\}$ is the driver's selection probability distribution, estimated from usage logs, with $\sum_{i=0}^{n-1} P_i = 1$. Intuitively, *Time-Cost* is lower when frequently needed buttons (P_i is high) are located in faster positions ($T_i^{(L)}$ is low), reflecting performance aligned with the driver's profile.

In our framework, the inputs $T_i^{(L)}$ to the model are obtained from the *Observation* phase: for each layout and button, we estimate $T_i^{(L)}$ from the observed selection times and compute the expected value for a given driver profile $\mathbf{P}$. To ensure the reliability of the expected-value computation in the *Time-Cost* model, it is necessary to verify that the estimated inputs $T_i^{(L)}$ are consistent with established models of human performance. Concretely, we evaluated whether the trial-level selection times underlying $T_i^{(L)}$ conformed to (1) the number of visible alternatives on the current page, as predicted by the Hick-Hyman law [49, 54], and (2) pointing difficulty as captured by the effective index of difficulty in Fitts's law [29, 30, 78, 110]. We derived a linear mixed model based on these assumptions, following Bernhaupt et al.'s [7] combined model approach, and used it to assess the structural validity of the $T_i^{(L)}$ values that serve as inputs to our *Time-Cost* model. Below, we describe the two models used for the structural validity approach, the Hick-Hyman law and Fitts's law, outline the structure of the constructed linear mixed model, and present analyses examining whether $T_i^{(L)}$ aligns with these two fundamental laws of human performance.

Baseline models: choice, pointing, and page progression. The Hick-Hyman law [49, 54] characterizes the time to choose among N alternatives as increasing logarithmically with N:

$$\mathrm{RT} = a + b \log_2(N + 1), \tag{2}$$

where RT is choice reaction time and a and b are empirically determined regression coefficients. We therefore define a layout-level Hick term $Hick^{(L)}$ as:

$$Hick^{(L)} = \log_2(N^{(L)} + 1), \tag{3}$$

where $N^{(L)}$ denotes the number of buttons visible on the current page under layout L, and expect that, all else being equal, selection time will increase with $Hick^{(L)}$.

Next, Fitts's law [29] describes how aimed pointing time scales with the ratio of movement distance A to target size W. For our 2D touchscreen endpoints, rather than using the spread along a single movement axis, we follow centroid-based formulations of endpoint variability for two-dimensional pointing tasks [115] and compute a bivariate endpoint standard deviation $SD_{x,y}$ around the centroid $(\bar{x}, \bar{y})$:

$$SD_{x,y} = \sqrt{\frac{1}{N-1} \sum_{i=0}^{N-1} \left[(x_i - \bar{x})^2 + (y_i - \bar{y})^2 \right]}. \tag{4}$$

We then obtain Crossman's effective target width W_e [17] from this bivariate spread:

$$W_e = 4.133 \cdot SD_{x,y}. \tag{5}$$

The corresponding effective index of difficulty for that button is therefore:

$$ID_e = \log_2\left(\frac{A}{W_e} + 1\right). \tag{6}$$

We refer to this effective index of difficulty as $Fitts^{(L,i)}$ for layout L and button i:

$$Fitts^{(L,i)} = ID_e^{(L,i)} = \log_2\left(\frac{A^{(L,i)}}{W_e^{(L,i)}} + 1\right), \tag{7}$$

where $A^{(L,i)}$ is the movement distance to button and $W_e^{(L,i)}$ is the effective target width of the button i in layout L. Under Fitts's law, movement time is expected to increase approximately linearly with $Fitts^{(L,i)}$. Thus, if pointing difficulty meaningfully constrains our selection times, we should observe longer times for targets with larger Fitts terms.

Additionally, our multi-page layout setup introduces an additional structural factor: page progression. For a layout L with $K^{(L)}$ pages, suppose target i appears on page $k \in \{1, \ldots, K^{(L)}\}$. We define the page depth of that target $Depth^{(L,i)}$ as:

$$Depth^{(L,i)} = k - 1, \tag{8}$$

which corresponds to the minimum number of page transitions required to reach its page from the first page. If navigation and place-keeping across pages are costly, then we expect selection time to grow with $Depth^{(L,i)}$ after controlling for the number of buttons on a page.

Deriving the mixed-effects model for trial-level selection time. To formalize how trial-level selection times depend on layout structure and cognitive load, we specified the following linear mixed-effects model for trial-level selection time T_{trial}:

$$\begin{aligned} T_{trial} = \; & \alpha + \gamma \, Load \\ & + \beta_H \, Hick^{(L)} + \beta_F \, Fitts^{(L,i)} + \beta_D \, Depth^{(L,i)} \\ & + \delta_H \left(Load \cdot Hick^{(L)} \right) + \delta_F \left(Load \cdot Fitts^{(L,i)} \right) \\ & + \delta_D \left(Load \cdot Depth^{(L,i)} \right) + u_{\mathrm{PID}} + \epsilon_{trial}, \end{aligned} \tag{9}$$

where α is the baseline selection time under low cognitive load for an average layout and button, γ is the additive cost of high cognitive load, *Load* is a binary factor indicating cognitive load (low = 0, high = 1), $\beta_H, \beta_F, \beta_D$ are the main-effect slopes for the Hick-Hyman term, the Fitts term, and Depth term, respectively, and $\delta_H, \delta_F, \delta_D$ capture how each slope changes under high load. The term u_{PID} is a random intercept for each participant, modeling between-participant differences in overall speed, and ϵ_{trial} is residual error at the trial level.

Table 4: Fixed-effect estimates for the Hick–Fitts–page-depth mixed-effects model (Equation 9). Predictors are z-scored; Load $= 0$ for Low load and Load $= 1$ for High load.

Predictor	Estimate	SE	t	p
Intercept	2.406	0.129	18.674	$< .001$
Load	0.430	0.045	9.651	$< .001$
Hick	0.135	0.040	3.425	$< .001$
Fitts	0.012	0.033	0.372	.710
Depth	0.852	0.040	21.552	$< .001$
Load × Hick	−0.005	0.056	−0.096	.731
Load × Fitts	−0.083	0.045	−1.834	.067
Load × Depth	0.016	0.056	0.284	.776

Model fit: strong Hick-Hyman and page-depth effects, limited Fitts's law effect. We fit the model in Equation 9 to the touch selection times from the *Observation* phase. As a result, *Load* has a robust positive effect on selection time, consistent with the NASA-TLX results and our decision to treat cognitive load as a separate factor in the *Time-Cost* formulation. Next, the *Hick* term and *Depth* term both exhibit strong, significant positive effects ($\beta_H = 0.135$, $\beta_D = 0.852$, both $p < .001$), and their interactions with *Load* are negligible. This indicates that the trial-level selection times underlying $T_i^{(L)}$ increase systematically with both the number of on-screen alternatives and page depth, in line with the qualitative predictions of the Hick–Hyman law and our page-progression definition.

By contrast, the *Fitts* term shows a small, non-significant main effect ($\beta_F = 0.012$, $p = .710$) and *Load* × *Fitts* interaction ($\delta_F = -0.083$, $p = .067$). After accounting for *Hick* and *Depth*, only a limited portion of the remaining variance in selection time is attributable to the effective index of difficulty from Fitts's law. Overall, the mixed-effects results suggest that our empirically estimated $T_i^{(L)}$ values are primarily organized by choice complexity and page progression, with pointing difficulty contributing at most a secondary effect in this dual-task driving setting.

These findings indicate that our *Time-Cost* model is not significantly supported by the effective index of difficulty from Fitts's law. However, prior work combining pointing tasks with simulated driving has shown that Fitts's-law relationships often weaken or break down under dual-task driving conditions. Studies comparing single-task pointing with pointing while driving report clear linear relationships between movement time and ID_e in single-task settings, but greatly reduced or absent sensitivity to ID_e when steering and gaze shifts are integrated into the movement [98]. Our mixed-effects results are consistent with this literature: in our data, page-level structure and cognitive load dominate, and the Fitts term plays only a minor role once those factors are controlled.

Taken together, these analyses support the structural validity of the model; the $T_i^{(L)}$ values follow a structure broadly consistent with classic models of human performance. They increase in accordance with the Hick–Hyman law, rising with the information-theoretic difficulty of choosing among many on-screen alternatives and with page depth, while the effective index of difficulty from Fitts's law contributes comparatively little in the dual-task driving context, consistent with prior findings. The *Time-Cost* model therefore combines a standard expected-cost formulation with per-target time estimates whose dependence on layout structure and cognitive load is grounded both in our empirical data and in prior work on choice, pointing, and multitasking in driving.

5.1.2 Demonstration of Time-Cost Model. To demonstrate practical applications, we implemented a tool embedding the empirical selection-time curves, which accepts an arbitrary probability vector $\mathbf{P}$ as input and computes T_c across the candidate layouts (4×4, 4×2, 2×2). We illustrate results with two prototypical distributions: (1) an *exponential* profile, where button selection probability decreases according to $P_i = \frac{e^{-\lambda i}}{\sum_{j=0}^{15} e^{-\lambda j}}$, with larger values of λ concentrating mass on a few top functions; and (2) a *step* profile, where the top-K buttons share equal probability ($1/K$) and the remainder have zero (Figure 9).

Figure 9 visualizes *Time-Cost* curves under varying exponential bases and step thresholds, respectively. Results show that when usage probability is concentrated on a small set of functions (large λ, small K), layouts with fewer, larger targets on the first page are more efficient, while broader distributions favor layouts with more targets per page to offset cumulative page-switching costs. For instance, when $\lambda \approx 1.2$, layouts maximizing first-page target salience minimize cost; when $\lambda \approx 0$, flatter distributions make the dense 4×4 grid preferable. Similarly, in the step profile, smaller K values favor layouts clustering top functions on the first page, whereas larger K values make dense grids more advantageous. However, unlike the exponential profile, the step profile exhibits discrete jumps in *Time-Cost* when the number of top-K buttons matches the number of buttons per page, producing cases where intermediate layouts such as 4×2 are the most effective (e.g., when $K = 8$). Thus, we numerically confirmed our co-design finding that the most effective layout varies according to the driver's profile—represented by the button selection probability distribution—and that applying a layout tailored to the profile can reduce the expected selection time, as quantified by the *Time-Cost* model.

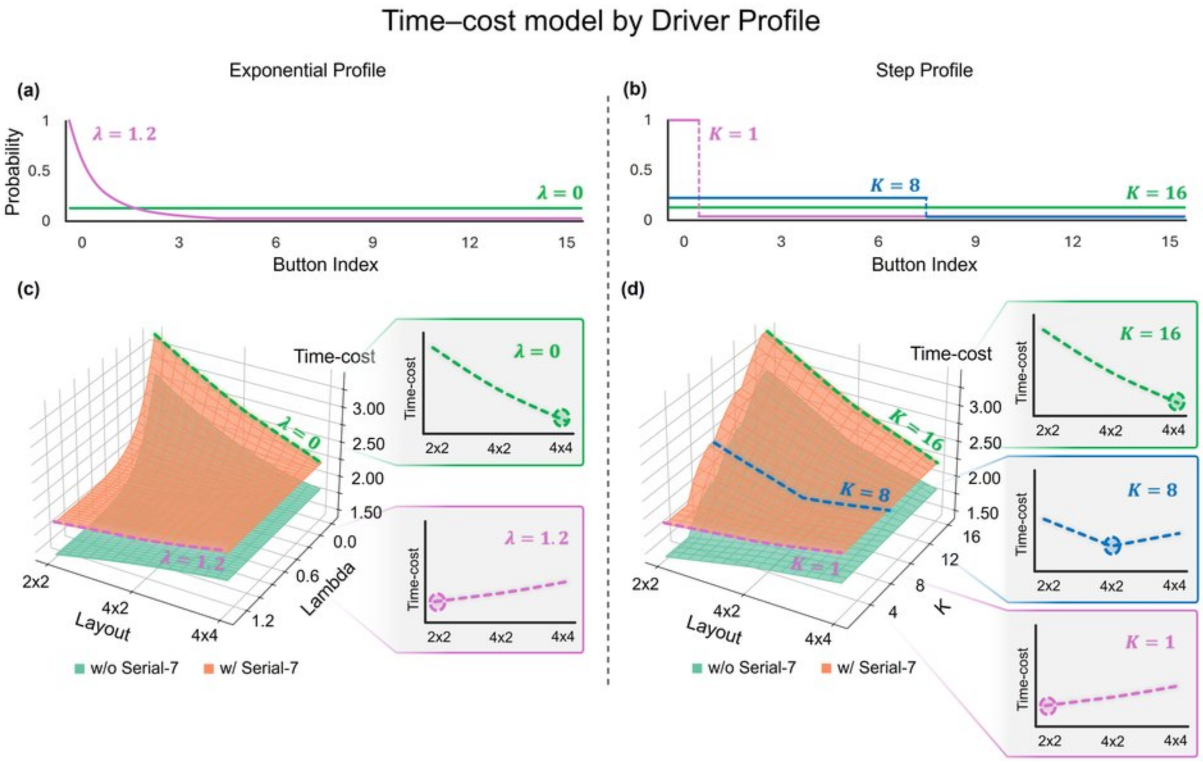


Figure 9: Time-Cost model under two driver profiles–exponential and step. Panels (a) and (b) show, for each profile, selection probability by button index across parameter settings (λ, K). Panels (c) and (d) present 3D surfaces of Time-Cost for each layout (2×2, 4×2, 4×4) as a function of the parameters, with the layout achieving the minimum Time-Cost at each setting indicated.

The contributions of this model are threefold. First, it computes optimal layouts transparently through an explainable cost function tailored to each driver's *Profile*, **P**. Second, it reuses empirical selection-time data from the *Observation* phase, requiring only domain-specific calibration for deployment. Third, it preserves predictability by updating layouts only when profile estimates converge beyond a stability threshold; otherwise, short-term adaptation is managed solely through state-based surface interventions. In sum, the *Time-Cost* model quantifies long-term *Profile* adaptation, providing principled, automated recommendations for when and how to adjust layouts.

5.2 Design Patterns for State-Based Real-Time Adaptation

Next, under the constraint of a stable interface layout, we propose real-time design patterns for state-based cosmetic adaptation to transient increases in cognitive load. Drawing on our Co-Design phase, we classify the design sketches developed with experts into design patterns that re-weight visual attention through cosmetic properties without relocating targets. All patterns comply with three rules: (1) no target relocation, (2) gradual entry and exit via subtle animations, and (3) hysteresis and buffering to suppress flicker and avoid temporal overlap with driving events. We categorize interventions into three channels—*boundary shapes* (B1 – B4, Figure 10), *graphics and icons* (G1 – G3, Figure 11), and *frame-preserving scaling* (F1 – F2, Figure 12):

- **B1–Highlight Ring**: Add highlighting around high-priority targets, scaled to the target's dimensions, with luminance contrast calibrated against the background for peripheral visibility.
- **B2–Background Attenuation**: Reduce saturation and slightly adjust brightness of non-essential elements to lessen visual salience, while preserving minimum readability thresholds.
- **B3–Glare-safe Luminance Upshift**: In low-light conditions, increase relative luminance without glare by adjusting background-relative brightness and fixing color temperature.
- **B4–Shape Accent**: Adjust corner radius to emphasize icon morphology without altering coordinates.

- **G1–Icon (Font)-Size Microstep**: Increment font size within fixed bounding boxes, redistributing padding to prevent overflow while maintaining legibility.
- **G2–Weight/Stroke Boost**: Increase text weight or icon stroke to improve prominence.
- **G3–Outline Overlay**: Add a semi-transparent outline, sampled from complementary background colors, to clarify boundaries in low-saturation themes.

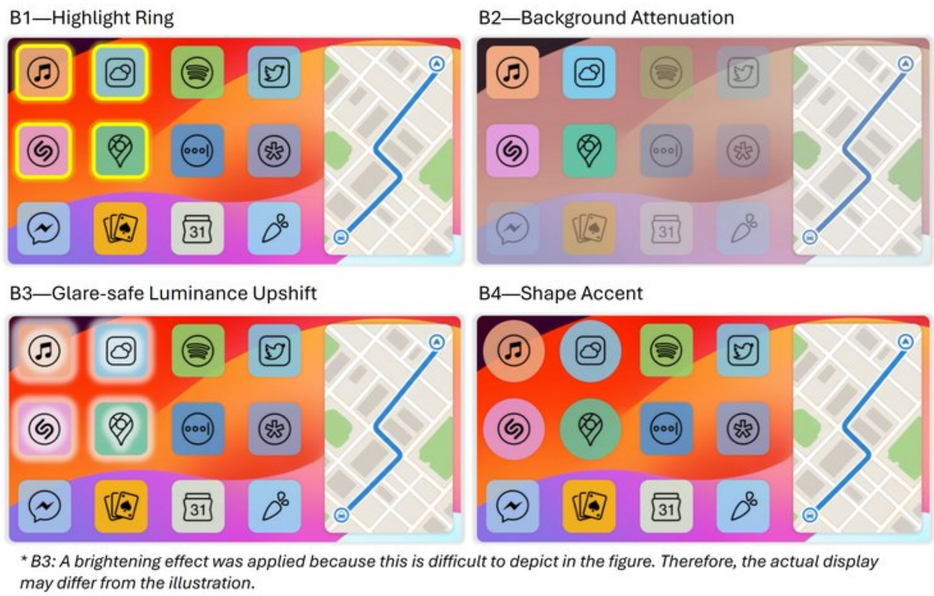


Figure 10: A design pattern that modulates visual weight by transforming boundary shapes.

Figure 11: A design pattern that modulates visual weight by transforming graphics and icons.

- **F1–Aux Viewport Compaction**: Temporarily shrink auxiliary areas (e.g., map, album art) via viewport scaling to allocate more space to key targets.
- **F2–Bounded Target Upscale**: Redistribute freed margins to enlarge high-priority targets while preserving spacing and safe margins.

The three channels are complementary rather than mutually exclusive and may be applied together when warranted. When combining boundary-shape cues with graphic/icon cues, a clear visual hierarchy should be coordinated so that one channel provides the primary emphasis while the other offers light support, avoiding redundant signals or localized clutter around targets. A consistent visual grammar and sufficient spacing should be preserved so that emphasis remains legible without competing edges or overlays. *Frame-preserving scaling* can be layered with the other channels and is expected to yield the largest change in visual weight. However, this scaling should be used conservatively to maintain predictability by keeping anchors stable, bounding the magnitude of change, and using smooth, non-disruptive transitions. Overall, the importance is to manage a limited salience budget across channels such that

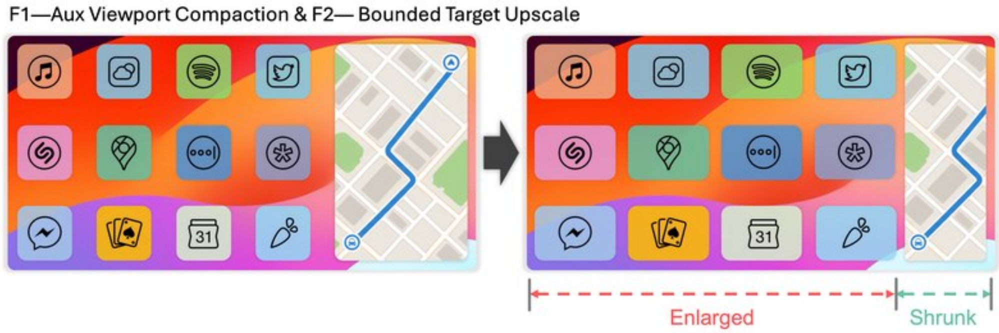


Figure 12: A design pattern that modulates visual weight by frame-preserving scaling.

their combined effect remains within a comfortable range while the underlying layout remains stable.

In summary, this proposal integrates long-term *Profile* adaptation through structural reconfigurations limited to change windows, while short-term *State* adaptation reallocates perceptual weight via a *focus-mode* that preserves spatial stability. The *Time-Cost* model enables transparent, quantitative decision-making for layout updates, whereas real-time *design patterns* incorporate hysteresis and event-gating to ensure stability.

6 Discussion

In this paper, we propose a *Profile-State Adaptive (PSA)* framework for in-vehicle touch interfaces, developed through a three-phase process—*Observation*, *Co-design*, and *Proposal*—and show that cognitive load and layout jointly shape selection time and glance behavior, that co-designed policies reconcile adaptability with stability, and that a *Time-Cost* model operationalizes profile-based layout selection. In this section, guided by the key PSA policies—long-term profile personalization and short-term state-based adjustments—we classify prior studies through a PSA lens (Section 6.1) and describe this paper's limitations and directions for future research (Section 6.2).

6.1 Positioning Prior Work Through the PSA Lens

Prior work has cautioned that fully adaptive behavior in unfamiliar contexts can raise workload and impair performance [68]. PSA directly operationalizes this caution by splitting adaptation across time scales: high-impact structural changes (grid, pagination, ordering, large size changes) are reserved for infrequent, profile-driven updates with previews and recovery; low-impact cosmetic adjustments (contrast, weight, bounded scaling) are permitted in real time when warranted by a person's state. This design rule preserves the familiar spatial frame while still offering timely assistance, reconciling adaptability with predictability.

6.1.1 The Profile Axis (Long-Term Structural Adaptation). Several systems personalize functionality or content to user preferences. For example, *CARSI II* recommends infotainment content based on context to increase user satisfaction [112], and *DriverSense* reconfigures smartphone UIs during driving according to environmental context and driver preferences [59]. Earlier perspectives on tailoring interfaces to user characteristics similarly motivate profile-level choices [1]. Viewed through PSA, these efforts instantiate profile-level adaptation (prioritizing what a given driver tends to need). However, their common limitation is that they do not explicitly manage temporal separation (when major structural changes should occur) or quantify layout time costs under paging and search.

Our PSA builds on this line of work by making layout structure an explicit, profile-dependent design variable rather than a fixed backdrop. Using the *Time-Cost* model grounded in our *Observation* phase, profile-based long-term adaptation projects each driver's button-selection probability distribution onto candidate layouts (2×2, 4×2, 4×4) and computes expected selection time given empirically observed page-transition penalties and target-size benefits. Structural updates are then restricted to low-demand change windows with previews and options to confirm, postpone, or revert, and core anchors such as home, back, and volume remain protected from relocation (see Section 4.3). In practical terms, the framework extends prior work arguing that interfaces should adapt to driver profiles by providing a quantitative procedure for determining which layout is appropriate for a given driver profile and when it is safe to propose structural changes.

6.1.2 The State-Axis (Short-Term Cosmetic Adaptation). A second line of work adapts interfaces to the driver's momentary workload or driving conditions. Meiser et al. present a workload-contingent automotive HMI that adapts to environment-induced mental workload [82]; Lavie et al. show that an adaptive in-vehicle telematics system can reduce task time and lane deviation [68]; *AdaptiveVoice* adjusts the brevity of voice interactions under high cognitive load [111]; hazard-contingent attenuation curbs distraction during risky moments [102]; and Galarza et al. connect predicted driving complexity to interface functionality [34, 35]. Through the PSA lens, these are exemplars of the state axis: they reduce near-term search or decision costs under specific circumstances, but typically leave the underlying layout and its long-term evolution outside the scope of the adaptation logic.

PSA ties state-based adaptation directly to the empirical effects of cognitive load and layout in the *Observation* phase: the Serial-7s task increased selection time and the number of screen transitions without changing overall off-road time (Sections 3.2.3 and 3.2.4). In response, PSA restricts state-based real-time adaptation to a conservative focus-mode that re-weights visual salience while keeping the layout fixed: high-priority targets receive modest highlighting or bounded enlargement, non-essential elements are attenuated without harming legibility, and low-urgency notifications are deferred to a "later" stack (Section 4.3). By extending prior state-aware systems, PSA introduces both long- and short-term time scales and, through co-design, proposes *how* to reshape salience under high cognitive load while preserving the profile-derived structure and spatial predictability.

6.1.3 The Adaptability-Stability Trade-Off. Prior work has cautioned that fully adaptive behavior in unfamiliar contexts can raise workload and injure performance [68]. PSA takes this caution as a design constraint by explicitly separating adaptation across time scales. High-impact structural changes (e.g., grid, pagination, ordering) are confined to infrequent, profile-driven update windows with previews and recovery options, whereas low-impact cosmetic adjustments (e.g., contrast, weight, bounded scaling) are the only changes permitted during driving in response to a driver's estimated state. By avoiding structural surprises in those moments and limiting in-drive adaptation to reversible cosmetic tweaks, the framework treats stability as an explicit boundary within which adaptation is allowed, aiming to preserve drivers' learned spatial map of the interface while still providing targeted, timely assistance.

6.1.4 Touchscreen Design Findings as PSA Model Terms. Evidence from prior work indicates that layout, target size/density, and menu depth/breadth shape glance behavior and task time: Distraction grows with greater road-touchscreen eccentricity [66, 113]; homepage partitioning alters glance metrics and lateral control [116]; deeper/broader menus slow completion and raise visual demand [40, 75]; traversal mechanics modulate glance variability [64, 65, 67]; larger/fewer targets improve efficiency [27, 63]; salience helps search but excessive density risks crowding [87, 105]; icon size/density/color drive perceived complexity [118]; and larger screens can induce fewer but longer glances [10, 76].

PSA does not replace these findings; it uses them as parameters in a model. The *Time-Cost* model combines these empirically observed per-page penalties and target-size effects with a driver's estimated selection probabilities to compute an expected time cost for each candidate layout. This lets designers compare a small library of layouts for a given profile using the same units that prior work optimizes, rather than relying only on generic heuristics. On the state side, PSA's focus-mode patterns draw on the same evidence about crowding and salience: cosmetic emphasis is limited to modest boosts for a few high-priority targets, so that additional highlighting does not push the screen into visually overloaded regimes known to lengthen visual search or increase glances.

6.1.5 Computational and Design Methodology Links. Classical models like *ACT-R* [4] and *GOMS* [14, 56] (and their automotive follow-ups [89]) provide principled accounts of scheduling visual/cognitive resources and decomposing tasks into operators. The community has also called for computational models whose predictions are explicitly tied to interface design and usable in practice [74]. PSA provides a concrete, bounded example of this link in the specific setting of in-vehicle touchscreens. Empirically grounded selection-time curves are summarized in our *Time-Cost* model that can be evaluated for each candidate layout given a driver's estimated selection probabilities, yielding directly comparable costs in the same units as our observational results. Designers can then use these costs to choose between a library of layouts for different driver profiles, rather than relying only on informal judgments about "flatter" or "denser" structures. On the design side, the co-design workshops do not stop at high-level themes: their outcomes are encoded as explicit policies in the PSA proposal. Together, these elements turn PSA from a descriptive framework into a set of model-informed, implementable rules for which layouts to favor and how adaptation is allowed to occur over time.

6.2 Future Work

Although our findings demonstrate the benefits of profile- and state-based adaptation, further research is needed to deploy and refine the PSA framework in real-world settings. An immediate next step is to evaluate these adaptive interface strategies in on-road driving scenarios or more dynamic simulation environments. Our study employed a simplified driving task to isolate secondary task performance; however, testing the PSA system with real traffic conditions, varied road conditions, and longer-term daily driving would verify that the observed benefits (e.g., shorter glance durations and quicker selections) translate into genuine safety improvements. Such studies could also uncover potential unintended driver responses or failure modes, ensuring the adaptive system is robust under diverse conditions before it is integrated into production vehicles.

We presented *Time–Cost* and state-adaptation design patterns as empirical examples that follow our co-designed guidelines, and we conducted a structural validation of the *Time–Cost* model. However, additional user-facing studies are still required. Beyond numerically validating the PSA model, such studies should evaluate the framework in more ecologically valid settings through the following: (1) conducting predictive validation by testing whether the *Time–Cost* model accurately forecasts selection times on held-out participants and longer-term logs; (2) running user studies that compare the PSA framework against strong static baselines and against ablations (profile-only, state-only), assessing their effects on safety-relevant metrics such as eyes-off-road measures, selection time, and driving errors; and (3) deploying the system in naturalistic field settings to examine the durability of benefits, trigger reliability, and hysteresis configurations over multiple weeks. For the design suggestions specifically, deeper research should integrate computational visual saliency models to tune highlight strength, contrast, size, and timing under in-vehicle viewing constraints (peripheral detectability, crowding, luminance, and motion). Psychophysical tasks (e.g., peripheral detection under brief glances) can additionally calibrate model parameters to driver- and context-specific thresholds, enabling a principled saliency budget that improves target detectability without introducing visual competition or glare. In addition, future work should incorporate multi-session, iterative, and reflective co-design engagements to revisit and refine the resulting concepts and sketches, as such follow-up discussions may surface insights that are unlikely to emerge within a single time-bounded session.

Future work should also extend the scope of state-based adaptation beyond the specific cognitive load paradigm used here. Our experiment induced high cognitive load via a mental arithmetic task; in practice, drivers may experience cognitive load due to factors like heavy traffic, pedestrians, emotional stress, fatigue, or multitasking (e.g., engaging in conversation) [9, 19, 77]. Investigating how the interface should adapt to these varying driver states is a logical progression. Advancing this line of work requires developing reliable real-time detection methods for different forms of driver strain, such as using eye-tracking measures, physiological signals, or driving performance indicators to trigger adaptation [60]. By broadening the types of driver state that the system can recognize and respond to, the adaptive UI can be made more universally responsive to distraction and workload.

Another important avenue is to explore driver acceptance and usability of adaptive interfaces over extended periods. Although our co-design emphasized minimizing disruption, drivers' trust in and satisfaction with an adaptive interface should be empirically studied. Longitudinal user studies could examine how drivers acclimate to infrequent layout changes (for example, when their profile-based layout updates after a software revision or a period of use) and whether they find the real-time *focus-mode* helpful or intrusive. User feedback can guide how much transparency or manual control over adaptation is needed—for instance, some drivers might appreciate notifications explaining a layout change or options to customize the degree of adaptation. Ensuring that adaptation strategies are intuitive and desirable to end-users will be key to their successful adoption.

Finally, the PSA framework can be expanded to encompass a wide range of interface modalities and design configurations. Future implementations might integrate multimodal feedback and controls, such as using auditory cues or haptic feedback [23, 24, 53, 69] in conjunction with visual changes to further reduce the need for visual attention. Additionally, our *Time-Cost* model and adaptation logic can be generalized beyond the specific grid layouts tested. More sophisticated algorithms could dynamically generate or adjust layouts for different screen sizes, numbers of functions, or even varying driving contexts (for example, simplifying the interface when the vehicle is in motion but restoring full functionality when stopped). Beyond conventional displays, an important direction is to investigate how PSA-style adaptation can be applied to in-car extended reality environments, which have recently attracted growing research interest [37, 38, 57, 58, 117]. Another extension is to study how adaptive UIs interact with advanced driver-assistance or semi-autonomous systems; as vehicles take on more driving tasks, the role of human-machine interface adaptation may need to evolve (for instance, easing the transition of control between automated systems and the driver) [61, 62]. In summary, continued research should focus on validating the PSA approach in naturalistic conditions, enriching the adaptation triggers and modalities, and ensuring that the system remains user-centered. These efforts will help bring adaptive automotive interfaces from concept to a safe and effective reality.

7 Conclusion

Our study introduced a *Profile-State Adaptive (PSA)* framework for designing in-vehicle adaptive user interfaces that balances long-term structural adaptations with short-term cosmetic adaptations. We employed a three-phase process and described how the PSA framework balances driver-specific behaviors with moment-to-moment changes in cognitive demands. In the *Observation* phase, we quantified the impact of cognitive load on touchscreen interactions and gaze patterns, exploring how this impact is modulated by different interface layouts. In the *Co-design* phase, experts converged on design guidelines for in-cabin adaptive user interfaces, accounting for adaptability-stability tradeoffs, separating long-term profile-based adaptations from short-term state-based adaptations, and accounting for cross-cutting requirements. In the *Proposal* phase, we operationalized the PSA framework via a data-driven *Time-Cost* model that projects a driver's target selection probability distribution onto empirical selection-time curves to identify ideal long-term layouts for different driver profiles, and a framework to select real-time cosmetic adaptations that preserve layout characteristics while adjusting perceptual salience. Together, these components provide data-backed policies and tools that help guide how in-vehicle UIs should adapt both to people and their cognitive state, allowing a balance of both rich but safe interactions.

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References

[1] Demosthenes Akoumianakis and Constantine Stephanidis. 1997. Supporting user-adapted interface design: The USE-IT System. *Interacting with computers* 9, 1 (1997), 73–104.
[2] Gila Albert, Oren Musicant, Ilit Oppenheim, and Tsippy Lotan. 2016. Which smartphone's apps may contribute to road safety? An AHP model to evaluate experts' opinions. *Transport Policy* 50 (2016), 54–62.
[3] Robert St Amant, Thomas E Horton, and Frank E Ritter. 2007. Model-based evaluation of expert cell phone menu interaction. *ACM Transactions on Computer-Human Interaction (TOCHI)* 14, 1 (2007), 1–es.
[4] John R Anderson, Michael Matessa, and Christian Lebiere. 1997. ACT-R: A theory of higher level cognition and its relation to visual attention. *Human–Computer Interaction* 12, 4 (1997), 439–462.
[5] Kristen E Beede and Steven J Kass. 2006. Engrossed in conversation: The impact of cell phones on simulated driving performance. *Accident Analysis & Prevention* 38, 2 (2006), 415–421.
[6] Simone Benedetto, Marco Pedrotti, Roland Bremond, and Thierry Baccino. 2013. Leftward attentional bias in a simulated driving task. *Transportation research part F: traffic psychology and behaviour* 20 (2013), 147–153.
[7] Regina Bernhaupt, Girish Dalvi, Anirudha Joshi, Devanuj K Balkrishan, Jacki O'Neill, and Marco Winckler. 2017. *Human-Computer Interaction-INTERACT 2017: 16th IFIP TC 13 International Conference, Mumbai, India, September 25-29, 2017, Proceedings, Part II*. Vol. 10514. Springer.
[8] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative research in psychology* 3, 2 (2006), 77–101.
[9] David P Broadbent, Giorgia D'Innocenzo, Toby J Ellmers, Justin Parsler, Andre J Szameitat, and Daniel T Bishop. 2023. Cognitive load, working memory capacity and driving performance: A preliminary fNIRS and eye tracking study. *Transportation research part F: traffic psychology and behaviour* 92 (2023), 121–132.
[10] Timothy Brown, Dawn Marshall, and Neil Lerner. 2019. Comparing performance when using a new style large touchscreen compared to a traditional in-vehicle touchscreen. In *Driving Assessment Conference*, Vol. 10. University of Iowa.
[11] Totsapon Butmee, Terry C Lansdown, and Guy H Walker. 2019. Mental workload and performance measurements in driving task: A review literature. In

Proceedings of the 20th Congress of the International Ergonomics Association (IEA 2018) Volume VI: Transport Ergonomics and Human Factors (TEHF), Aerospace Human Factors and Ergonomics 20. Springer, 286–294.

[12] Jeff K Caird, Sarah M Simmons, Katelyn Wiley, Kate A Johnston, and William J Horrey. 2018. Does talking on a cell phone, with a passenger, or dialing affect driving performance? An updated systematic review and meta-analysis of experimental studies. *Human factors* 60, 1 (2018), 101–133.

[13] Yusheng Cao, Lingyu Li, Jiehao Yuan, and Myounghoon Jeon. 2025. Head-up Displays Improve Drivers' Performance and Subjective Perceptions with the In-Vehicle Gesture Interaction System. *International Journal of Human–Computer Interaction* 41, 11 (2025), 6921–6935.

[14] Stuart K Card. 2018. *The psychology of human-computer interaction.* Crc Press.

[15] William S Cleveland. 1979. Robust locally weighted regression and smoothing scatterplots. *Journal of the American statistical association* 74, 368 (1979), 829–836.

[16] Council of European Union. 2019. Council regulation (EU) no 2019/2144. https://eur-lex.europa.eu/eli/reg/2019/2144/oj.

[17] ERFW Crossman. 1957. The speed and accuracy of simple hand movements. *The nature and acquisition of industrial skills* (1957).

[18] David Crundall and Geoffrey Underwood. 2011. Visual attention while driving: measures of eye movements used in driving research. In *Handbook of traffic psychology*. Elsevier, 137–148.

[19] Gianluca Di Flumeri, Gianluca Borghini, Pietro Aricò, Nicolina Sciaraffa, Paola Lanzi, Simone Pozzi, Valeria Vignali, Claudio Lantieri, Arianna Bichicchi, Andrea Simone, et al. 2018. EEG-based mental workload neurometric to evaluate the impact of different traffic and road conditions in real driving settings. *Frontiers in human neuroscience* 12 (2018), 509.

[20] Alexey Dosovitskiy, German Ros, Felipe Codevilla, Antonio Lopez, and Vladlen Koltun. 2017. CARLA: An open urban driving simulator. In *Conference on robot learning*. PMLR, 1–16.

[21] Martin Dostál. 2010. User acceptance of the microsoft Ribbon user interface. In *Proceedings of the 9th WSEAS International Conference on Data Networks, Communications, Computers* (Faro, Portugal) *(DNCOCO'10)*. World Scientific and Engineering Academy and Society (WSEAS), Stevens Point, Wisconsin, USA, 143–149.

[22] Ernest Edmonds. 1993. The future of intelligent interfaces: not just "how?", but "what?" and "why?". In *Proceedings of the 1st international conference on Intelligent user interfaces*. 13–17.

[23] Ahmed Elsharkawy, Aya Ataya, Dohyeon Yeo, Minwoo Seong, Seokhyun Hwang, Joseph DelPreto, Wojciech Matusik, Daniela Rus, and SeungJun Kim. 2024. Adaptive In-Vehicle Virtual Reality for Reducing Motion Sickness: Manipulating Passenger Posture During Driving Events. In *Companion of the 2024 on ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 832–836.

[24] Ahmed Ibrahim Ahmed Mohamed Elsharkawy, Aya Abdulnasser Saed Ataya, Dohyeon Yeo, Eunsol An, Seokhyun Hwang, and SeungJun Kim. 2024. Sync-vr: Synchronizing your senses to conquer motion sickness for enriching in-vehicle virtual reality. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems*. 1–17.

[25] Johan Engström, Emma Johansson, and Joakim Östlund. 2005. Effects of visual and cognitive load in real and simulated motorway driving. *Transportation research part F: traffic psychology and behaviour* 8, 2 (2005), 97–120.

[26] Julian J Faraway. 2016. *Extending the linear model with R: generalized linear, mixed effects and nonparametric regression models.* Chapman and Hall/CRC.

[27] Fred Feng, Yili Liu, and Yifan Chen. 2018. Effects of quantity and size of buttons of in-vehicle touch screen on drivers' eye glance behavior. *International Journal of Human–Computer Interaction* 34, 12 (2018), 1105–1118.

[28] Leah Findlater and Joanna McGrenere. 2008. Impact of screen size on performance, awareness, and user satisfaction with adaptive graphical user interfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Florence, Italy) *(CHI '08)*. Association for Computing Machinery, New York, NY, USA, 1247–1256. doi:10.1145/1357054.1357249

[29] Paul M Fitts. 1954. The information capacity of the human motor system in controlling the amplitude of movement. *Journal of experimental psychology* 47, 6 (1954), 381.

[30] Paul M Fitts and James R Peterson. 1964. Information capacity of discrete motor responses. *Journal of experimental psychology* 67, 2 (1964), 103.

[31] Umberto Fugiglando, Emanuele Massaro, Paolo Santi, Sebastiano Milardo, Kacem Abida, Rainer Stahlmann, Florian Netter, and Carlo Ratti. 2018. Driving behavior analysis through CAN bus data in an uncontrolled environment. *IEEE Transactions on Intelligent Transportation Systems* 20, 2 (2018), 737–748.

[32] Krzysztof Z Gajos, Jing Jing Long, and Daniel S Weld. 2006. Automatically generating custom user interfaces for users with physical disabilities. In *Proceedings of the 8th International ACM SIGACCESS Conference on Computers and Accessibility*. 243–244.

[33] Krzysztof Z Gajos, Daniel S Weld, and Jacob O Wobbrock. 2010. Automatically generating personalized user interfaces with Supple. *Artificial intelligence* 174, 12-13 (2010), 910–950.

[34] Miguel Galarza and Josep Paradells. 2019. Improving road safety and user experience by employing dynamic in-vehicle information systems. *IET Intelligent Transport Systems* 13, 4 (2019), 738–744.

[35] Miguel Angel Galarza, Teresa Bayona, and Josep Paradells. 2017. Integration of an adaptive infotainment system in a vehicle and validation in real driving scenarios. *International journal of vehicular technology* 2017, 1 (2017), 4531780.

[36] Pnina Gershon, Kellienne R Sita, Chunming Zhu, Johnathon P Ehsani, Sheila G Klauer, Tom A Dingus, and Bruce G Simons-Morton. 2019. Distracted driving, visual inattention, and crash risk among teenage drivers. *American journal of preventive medicine* 56, 4 (2019), 494–500.

[37] Bocheon Gim, Seokhyun Hwang, Seongjun Kang, Gwangbin Kim, Dohyeon Yeo, and Seungjun Kim. 2025. I Want to Break Free: Enabling User-Applied Active Locomotion in In-Car VR through Contextual Cues. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. 1–19.

[38] Bocheon Gim, Seongjun Kang, Gwangbin Kim, Dohyeon Yeo, Seokhyun Hwang, and Seungjun Kim. 2024. Curving the virtual route: Applying redirected steering gains for active locomotion in in-car vr. In *Extended Abstracts of the CHI Conference on Human Factors in Computing Systems*. 1–7.

[39] Courtney M Goodridge, Rafael C Goncalves, Ali Arabian, Anthony Horrobin, Albert Solernou, Yee Thung Lee, Yee Mun Lee, Ruth Madigan, and Natasha Merat. 2024. Gaze entropy metrics for mental workload estimation are heterogenous during hands-off level 2 automation. *Accident Analysis & Prevention* 202 (2024), 107560.

[40] Hilkka Grahn and Tuomo Kujala. 2020. Impacts of touch screen size, user interface design, and subtask boundaries on in-car task's visual demand and driver distraction. *International Journal of Human-Computer Studies* 142 (2020), 102467.

[41] Lisa Graichen, Matthias Graichen, and Josef F Krems. 2019. Evaluation of gesture-based in-vehicle interaction: user experience and the potential to reduce driver distraction. *Human factors* 61, 5 (2019), 774–792.

[42] Joan Greenbaum and Morten Kyng. 2020. *Design at work: Cooperative design of computer systems*. CRC Press.

[43] Feng Guo, Sheila G Klauer, Youjia Fang, Jonathan M Hankey, Jonathan F Antin, Miguel A Perez, Suzanne E Lee, and Thomas A Dingus. 2017. The effects of age on crash risk associated with driver distraction. *International journal of epidemiology* 46, 1 (2017), 258–265.

[44] Arman Hafizi, Jay Henderson, Ali Neshati, Wei Zhou, Edward Lank, and Daniel Vogel. 2023. In-vehicle performance and distraction for midair and touch directional gestures. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–13.

[45] Joanne L Harbluk, Y Ian Noy, Patricia L Trbovich, and Moshe Eizenman. 2007. An on-road assessment of cognitive distraction: Impacts on drivers' visual behavior and braking performance. *Accident Analysis & Prevention* 39, 2 (2007), 372–379.

[46] Sandra G Hart. 2006. NASA-task load index (NASA-TLX); 20 years later. In *Proceedings of the human factors and ergonomics society annual meeting*, Vol. 50. Sage publications Sage CA: Los Angeles, CA, 904–908.

[47] Sandra G Hart and Lowell E Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In *Advances in psychology*. Vol. 52. Elsevier, 139–183.

[48] Arne Helland, Gunnar D Jenssen, Lone-Eirin Lervåg, Andreas Austgulen Westin, Terje Moen, Kristian Sakshaug, Stian Lydersen, Jørg Mørland, and Lars Slørdal. 2013. Comparison of driving simulator performance with real driving after alcohol intake: A randomised, single blind, placebo-controlled, cross-over trial. *Accident Analysis & Prevention* 53 (2013), 9–16.

[49] William E Hick. 1952. On the rate of gain of information. *Quarterly Journal of experimental psychology* 4, 1 (1952), 11–26.

[50] James J Higgins, R Clifford Blair, and Suleiman Tashtoush. 1990. The aligned rank transform procedure. (1990).

[51] James J Higgins and Suleiman Tashtoush. 1994. An aligned rank transform test for interaction. *Nonlinear World* 1, 2 (1994), 201–211.

[52] Amy Hurst, Jennifer Mankoff, Anind K. Dey, and Scott E. Hudson. 2007. Dirty desktops: using a patina of magnetic mouse dust to make common interactor targets easier to select. In *Proceedings of the 20th Annual ACM Symposium on User Interface Software and Technology* (Newport, Rhode Island, USA) *(UIST '07)*. Association for Computing Machinery, New York, NY, USA, 183–186. doi:10.1145/1294211.1294242

[53] Seokhyun Hwang, Seongjun Kang, Jeongseok Oh, Jeongju Park, Semoo Shin, Yiyue Luo, Joseph DelPreto, Sangbeom Lee, Kyoobin Lee, Wojciech Matusik, et al. 2025. TelePulse: Enhancing the Teleoperation Experience through Biomechanical Simulation-Based Electrical Muscle Stimulation in Virtual Reality. In *Proceedings of the 2025 CHI Conference on Human Factors in Computing Systems*. 1–26.

[54] Ray Hyman. 1953. Stimulus information as a determinant of reaction time. *Journal of experimental psychology* 45, 3 (1953), 188.

[55] Anthony Jameson. 2007. Adaptive interfaces and agents. In *The human-computer interaction handbook*. CRC press, 459–484.

[56] Bonnie E John and David E Kieras. 1994. *The GOMS family of analysis techniques: Tools for design and evaluation.* Technical Report.

[57] Yumin Kang, SeongA Choi, Eunsol An, Seokhyun Hwang, and Seungjun Kim. 2023. Designing virtual agent human–machine interfaces depending on the communication and anthropomorphism levels in augmented reality. In *Proceedings of the 15th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. 191–201.

[58] Yumin Kang, Jeongju Park, Seokhyun Hwang, Minwoo Seong, Gwangbin Kim, and SeungJun Kim. 2025. You're the One Whom I'm Talking To: The Role of Contextual External Human-Machine Interfaces in Multi-Road User Conflict Scenarios. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 9, 3 (2025), 1–37.

[59] Inayat Khan and Shah Khusro. 2020. Towards the design of context-aware adaptive user interfaces to minimize drivers' distractions. *Mobile Information Systems* 2020, 1 (2020), 8858886.

[60] Gwangbin Kim, Seokhyun Hwang, Minwoo Seong, Dohyeon Yeo, Daniela Rus, and SeungJun Kim. 2024. TimelyTale: a multimodal dataset approach to assessing passengers' explanation demands in highly automated vehicles. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 8, 3 (2024), 1–60.

[61] Gwangbin Kim and SeungJun Kim. 2025. Human-centric Intelligibility for Automated Vehicles: Aligning Explanations with Predictive Models of Passenger State. In *Companion of the 2025 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. 465–470.

[62] Gwangbin Kim, Dohyeon Yeo, Taewoo Jo, Daniela Rus, and SeungJun Kim. 2025. Decoding Your Ride: What Information Builds Human Trust on Real Roads? *GetMobile: Mobile Computing and Communications* 29, 2 (2025), 5–9.

[63] Heejin Kim. 2015. The effect of touch-key size on the usability of In-Vehicle Information Systems and driving safety during simulated driving. *, Applied Ergonomics* 45, 1 (2015), 1.

[64] Tuomo Kujala. 2013. Browsing the information highway while driving: three in-vehicle touch screen scrolling methods and driver distraction. *Personal and ubiquitous computing* 17, 5 (2013), 815–823.

[65] Tuomo Kujala and Pertti Saariluoma. 2011. Effects of menu structure and touch screen scrolling style on the variability of glance durations during in-vehicle visual search tasks. *Ergonomics* 54, 8 (2011), 716–732.

[66] Dave Lamble, Matti Laakso, and Heikki Summala. 1999. Detection thresholds in car following situations and peripheral vision: Implications for positioning of visually demanding in-car displays. *Ergonomics* 42, 6 (1999), 807–815.

[67] Annegret Lasch and Tuomo Kujala. 2012. Designing browsing for in-car music player: effects of touch screen scrolling techniques, items per page and screen orientation on driver distraction. In *Proceedings of the 4th international conference on automotive user interfaces and interactive vehicular applications*. 41–48.

[68] Talia Lavie and Joachim Meyer. 2010. Benefits and costs of adaptive user interfaces. *International Journal of Human-Computer Studies* 68, 8 (2010), 508–524.

[69] Jieun Lee, Seokhyun Hwang, Kyunghwan Kim, and SeungJun Kim. 2022. Auditory and olfactory stimuli-based attractors to induce reorientation in virtual reality forward redirected walking. In *CHI conference on human factors in computing systems extended abstracts*. 1–7.

[70] Quentin Limbourg, Jean Vanderdonckt, Benjamin Michotte, Laurent Bouillon, and Víctor López-Jaquero. 2004. USIXML: A language supporting multi-path development of user interfaces. In *IFIP International Conference on Engineering for Human-Computer Interaction*. Springer, 200–220.

[71] Jason Lisseman, Lisa Diwischek, Stefanie Essers, and David Andrews. 2014. In-Vehicle Touchscreen Concepts Revisited: Approaches and Possibilities. *SAE International Journal of Passenger Cars-Electronic and Electrical Systems* 7, 2014-01-0266 (2014), 141–148.

[72] Google LLC. 2025. *Android Auto*. https://www.android.com/auto/ Official product page.

[73] Neha Lodha, Hwasil Moon, Changki Kim, Tanya Onushko, and Evangelos A Christou. 2016. Motor output variability impairs driving ability in older adults. *Journals of Gerontology Series A: Biomedical Sciences and Medical Sciences* 71, 12 (2016), 1676–1681.

[74] Martin Lorenz, Tiago Amorim, Debargha Dey, Mersedeh Sadeghi, and Patrick Ebel. 2024. Computational Models for In-Vehicle User Interface Design: A Systematic Literature Review. In *Proceedings of the 16th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. 204–215.

[75] Nicolas Louveton, Rod Mccall, and Thomas Engel. 2024. Designing touchscreen menu interfaces for in-vehicle infotainment systems: The effect of depth and breadth trade-off and task types on visual-manual distraction. (2024).

[76] Jun Ma, Junyi Li, Zaiyan Gong, and Jihong Yu. 2017. *Impact of in-vehicle touchscreen size on visual demand and usability*. Technical Report. SAE Technical Paper.

[77] Jun Ma, Yiping Wu, Jian Rong, and Xiaohua Zhao. 2023. A systematic review on the influence factors, measurement, and effect of driver workload. *Accident Analysis & Prevention* 192 (2023), 107289.

[78] I Scott MacKenzie. 1992. Fitts' law as a research and design tool in human-computer interaction. *Human-computer interaction* 7, 1 (1992), 91–139.

[79] H Mansouri. 1998. Multifactor analysis of variance based on the aligned rank transform technique. *Computational statistics & data analysis* 29, 2 (1998), 177–189.

[80] Stefan Mattes. 2003. The lane-change-task as a tool for driver distraction evaluation. *Quality of Work and Products in Enterprises of the Future* 57, 60 (2003), 7.

[81] Joanna McGrenere, Ronald M. Baecker, and Kellogg S. Booth. 2007. A field evaluation of an adaptable two-interface design for feature-rich software. *ACM Trans. Comput.-Hum. Interact.* 14, 1 (May 2007), 3–es. doi:10.1145/1229855.1229858

[82] Elena Meiser, Alexandra Alles, Samuel Selter, Marco Molz, Amr Gomaa, and Guillermo Reyes. 2022. In-Vehicle Interface Adaptation to Environment-Induced Cognitive Workload. In *Adjunct Proceedings of the 14th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. 83–86.

[83] Evonne Miller. 2024. Thinking Differently: Six Principles for Crafting Rapid Co-design and Design Thinking Sprints as 'Transformative Learning Experiences in Healthcare'. In *How Designers Are Transforming Healthcare*. Springer, 265–279.

[84] Catalina Naranjo-Bock. 2012. Creativity-based Research: The Process of Co-Designing with Users. *UX Magazine* (24 April 2012). https://uxmag.com/articles/creativity-based-research-the-process-of-co-designing-with-users Accessed: 2025-11-15.

[85] Mélanie Née, Benjamin Contrand, Ludivine Orriols, Cédric Gil-Jardiné, Cédric Galéra, and Emmanuel Lagarde. 2019. Road safety and distraction, results from a responsibility case-control study among a sample of road users interviewed at the emergency room. *Accident Analysis & Prevention* 122 (2019), 19–24.

[86] Jianwei Niu, Xiai Wang, Xingguo Liu, Dan Wang, Hua Qin, and Yunhong Zhang. 2019. Effects of mobile phone use on driving performance in a multiresource workload scenario. *Traffic injury prevention* 20, 1 (2019), 37–44.

[87] Hans-Christoph Nothdurft. 2000. Salience from feature contrast: Variations with texture density. *Vision research* 40, 23 (2000), 3181–3200.

[88] Oscar Oviedo-Trespalacios, Mark King, Atiyeh Vaezipour, and Verity Truelove. 2019. Can our phones keep us safe? A content analysis of smartphone applications to prevent mobile phone distracted driving. *Transportation research part F: traffic psychology and behaviour* 60 (2019), 657–668.

[89] Junho Park and Maryam Zahabi. 2024. A review of human performance models for prediction of driver behavior and interactions with in-vehicle technology. *Human factors* 66, 4 (2024), 1249–1275.

[90] Antoine Ponsard and Joanna McGrenere. 2016. Anchored Customization: Anchoring Settings to the Application Interface to Afford Customization. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 4154–4165. doi:10.1145/2858036.2858129

[91] Pupil Labs GmbH. 2025. Neon Documentation. https://docs.pupil-labs.com/neon/. Accessed: 2025-11-13.

[92] Pupil Labs GmbH. 2025. Neon: Eye Tracking for Research and Beyond. https://pupil-labs.com/products/neon. Accessed: 2025-11-13.

[93] Bryan Reimer. 2009. Impact of cognitive task complexity on drivers' visual tunneling. *Transportation Research Record* 2138, 1 (2009), 13–19.

[94] Meghan Rogers, Yu Zhang, David Kaber, Yulan Liang, and Shruti Gangakhedkar. 2011. The effects of visual and cognitive distraction on driver situation awareness. In *International Conference on Engineering Psychology and Cognitive Ergonomics*. Springer, 186–195.

[95] Ling Rothrock, Richard Koubek, Frederic Fuchs, Michael Haas, and Gavriel Salvendy. 2002. Review and reappraisal of adaptive interfaces: toward biologically inspired paradigms. *Theoretical issues in ergonomics science* 3, 1 (2002), 47–84.

[96] Annie Rydström and Peter Bengtsson. 2008. The impact of haptic and visual secondary tasks on drivers' visual behaviour and driving performance: a qualitative analysis. In *International Conference on Applied Human Factors and Ergonomics: 14/07/2008-17/07/2008*. USA Publishing.

[97] Pavan Kumar Sharma and Pranamesh Chakraborty. 2024. A review of driver gaze estimation and application in gaze behavior understanding. *Engineering Applications of Artificial Intelligence* 133 (2024), 108117.

[98] Xiyuan Shen, Seokhyun Hwang, Junhan Kong, Alexandre LS Filipowicz, Andrew Best, Jean Costa, Scott Carter, James Fogarty, and Jacob O Wobbrock. 2025. Touchscreens in Motion: Quantifying the Impact of Cognitive Load on Distracted Drivers. In *Proceedings of the 38th Annual ACM Symposium on User Interface Software and Technology*. 1–21.

[99] Aaron Smith. 1967. The serial sevens subtraction test. *Archives of Neurology* 17, 1 (1967), 78–80.

[100] Constantine Stephanidis. 2001. Adaptive techniques for universal access. *User modeling and user-adapted interaction* 11, 1 (2001), 159–179.

[101] Zhizhuo Su, Roger Woodman, Joseph Smyth, and Mark Elliott. 2023. The relationship between aggressive driving and driver performance: A systematic review with meta-analysis. *Accident Analysis & Prevention* 183 (2023), 106972.

[102] Patrick Tchankue, Janet Wesson, and Dieter Vogts. 2011. The impact of an adaptive user interface on reducing driver distraction. In *Proceedings of the 3rd international conference on automotive user interfaces and interactive vehicular applications*. 87–94.

[103] Jan Törnros. 1998. Driving behaviour in a real and a simulated road tunnel—a validation study. *Accident Analysis & Prevention* 30, 4 (1998), 497–503.

[104] James E Trumbly, Kirk P Arnett, and Peter C Johnson. 1994. Productivity gains via an adaptive user interface: an empirical analysis. *International Journal of Human-Computer Studies* 40, 1 (1994), 63–81.

[105] Björn NS Vlaskamp and Ignace Th C Hooge. 2006. Crowding degrades saccadic search performance. *Vision research* 46, 3 (2006), 417–425.

[106] John Von Neumann and Oskar Morgenstern. 2007. Theory of games and economic behavior: 60th anniversary commemorative edition. In *Theory of games and economic behavior*. Princeton university press.

[107] Zheng Wang, Satoshi Suga, Edric John Cruz Nacpil, Bo Yang, and Kimihiko Nakano. 2021. Effect of Adaptive and Fixed Shared Steering Control on Distracted Driver Behavior. *arXiv preprint arXiv:2106.03364* (2021).

[108] Zheng Wang, Satoshi Suga, Edric John Cruz Nacpil, Bo Yang, and Kimihiko Nakano. 2021. Effect of fixed and sEMG-based adaptive shared steering control on distracted driver behavior. *Sensors* 21, 22 (2021), 7691.

[109] Garrett Weinberg, Bret Harsham, and Zeljko Medenica. 2011. Evaluating the usability of a head-up display for selection from choice lists in cars. In *Proceedings of the 3rd International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. 39–46.

[110] Alan Traviss Welford. 1968. Fundamentals of skill. (1968).

[111] Shaoyue Wen, Songming Ping, Jialin Wang, Hai-Ning Liang, Xuhai Xu, and Yukang Yan. 2024. AdaptiveVoice: Cognitively Adaptive Voice Interface for Driving Assistance. In *Proceedings of the 2024 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '24)*. Association for Computing Machinery, New York, NY, USA, Article 253, 18 pages. doi:10.1145/3613904.3642876

[112] Marco Wiedner, Sreerag V Naveenachandran, Philipp Hallgarten, Satiyabooshan Murugaboopathy, and Emilio Frazzoli. 2024. CARSI II: A Context-Driven Intelligent User Interface. In *Adjunct Proceedings of the 16th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*. 128–135.

[113] Marc Wittmann, Miklós Kiss, Peter Gugg, Alexander Steffen, Martina Fink, Ernst Pöppel, and Hiroyuki Kamiya. 2006. Effects of display position of a visual in-vehicle task on simulated driving. *Applied ergonomics* 37, 2 (2006), 187–199.

[114] Jacob O Wobbrock, Leah Findlater, Darren Gergle, and James J Higgins. 2011. The aligned rank transform for nonparametric factorial analyses using only anova procedures. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 143–146.

[115] Jacob O Wobbrock, Kristen Shinohara, and Alex Jansen. 2011. The effects of task dimensionality, endpoint deviation, throughput calculation, and experiment design on pointing measures and models. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 1639–1648.

[116] Zhengxin Wu, Kaiyue Rao, Weixing Dou, Yixi Bao, and Tao Jin. 2025. The Effect of Touchscreen Layout Division on the Usability and Driving Safety of In-Vehicle Information Systems. *International Journal of Human–Computer Interaction* 41, 5 (2025), 3340–3351.

[117] Dohyeon Yeo, Gwangbin Kim, Minwoo Oh, Jeongju Park, Bocheon Gim, Seongjun Kang, Ahmed Elsharkawy, and SeungJun Kim. 2025. Attracar: Multi-sensory in-car vr with thermal, airflow, and motion feedback through built-in vehicle systems. In *Proceedings of the 38th Annual ACM Symposium on User Interface Software and Technology*. 1–20.

[118] Sol Hee Yoon, Ji Hyoun Lim, and Yong Gu Ji. 2015. Perceived visual complexity and visual search performance of automotive instrument cluster: A quantitative measurement study. *International Journal of Human-Computer Interaction* 31, 12 (2015), 890–900.

[119] Wei Yuan, Zhuofan Liu, and Rui Fu. 2018. Predicting Drivers' Eyes-Off-Road Duration in Different Driving Scenarios. *Discrete Dynamics in Nature and Society* 2018, 1 (2018), 3481628.