A Modeling & Simulation (M&S) Framework to Assess Navigational Benefit and Distraction Potential for Specific Service Signs using Simulated Driving Performance and Self-reported Cognition

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ABSTRACT

The complexity of the driving task continues to increase due to several factors, including advancement of new vehicle designs, and resulting increases in cognitive workload. *Specific Service Signs* are often introduced along the roadway to provide distinct navigational benefits (e.g., proactive assistance with travel decisions) for drivers. However, such signage may also inadvertently impose unnecessary distraction to the driving task. For these reasons, empirical studies are required (e.g., by transportation engineers, urban and regional planners, human factors experts, vehicle designers, educators) to evaluate the safety impacts (i.e., Navigational Benefit and Distraction Potential) associated with proposed roadway signage and other traffic control devices.

In this study, we have performed a comprehensive evaluation of a singular Specific Service Sign (SSS) on simulated driver performance. We have employed a high-fidelity Modeling & Simulation (M&S) framework to analyze driving scenarios of varying environment density, for which we developed a Safety Rating model and instituted appropriate statistical approaches to quantify and evaluate performance. We further issued static and dynamic surveys for assessment of comprehension that supply additional insights on how the SSS may impact drivers differently.

Based on our experimental observations: a) most drivers required glance durations that exceed accepted guidelines for safe following distance; b) the proposed SSS was rated as being low-moderate in terms of distraction potential, and c) below average in terms of navigation utility; d) increasing environment density in the vicinity of the proposed SSS has potential to impair safe driving performance. The paper concludes with a brief description of ongoing and forecasted extensions for the current work.

ABOUT THE AUTHORS

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INTRODUCTION AND BROADER IMPACTS

With almost 230 million licensed drivers and 3.2 trillion total miles driven annually (U.S. DOT, 2019a, 2019b), driver safety remains a public health priority. Highway traffic signs (e.g., see Figure 1) are often implemented to aid drivers with regional navigation (Babić et al., 2020). Although the Manual on Uniform Traffic Control Devices (MUTCD) (FHWA, 2012) has long served as a nationwide standard for roadway control device form/function (e.g., size, shape, color, text, logos, fonts), proposed roadside signage can unwillingly induce cognitive distraction resulting in unnecessary risk to public safety (Bendak & Al-Saleh, 2010).

Figure 1 – Diverse highway traffic sign types

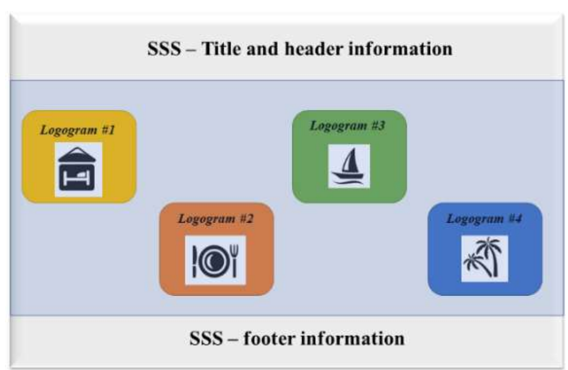

Figure 2 – Proposed SSS design (*notional*)

Specific Service Signs (SSS) are a specific type of roadway control device, and are defined (FHWA, 2012) as "guide signs that provide road users with directional information for services and attractions." Figure 2 illustrates a recently proposed SSS (**de-identified**), including a signage header (top), a signage footer (bottom), and primary navigational content in the body of the sign. Note that the proposed SSS contains four "logogram" panels each with text and colored icons to describe regional places of interest. To assess the navigational benefit (and the associated distraction potential) for the proposed SSS, we performed a Modeling & Simulation (M&S) evaluation on driver performance within scenarios of varying environment density. Our implementation was informed by guidelines to evaluate human factors associated with roadway signage (Hawkins & Rose, 2005), including the safe number of panels placed upon service signs (Dagnall et al., 2013) intended for regional attraction signs (Rasdorf et al., 2017), specifically. In our implementation, we developed a companion Safety Rating model to quantify and compare driver performance. We obtained self-report data to assess signage comprehension that supplies additional insight on how proposed SSS may impact drivers differently. We applied random parameter linear regression (Pang et al., 2022) to analyze the modeled safety ratings. The paper concludes with a brief description of planned extensions for the current work.

Please note that per sponsor request, the exact sign attributes (which have been introduced over the last decade) remain unidentified in this presentation and instead described in general terms. Despite this limitation, our overall framework, experimental implementation, and M&S methodology remain extensible towards the analysis of future traffic control device technologies for ongoing benefit to the broader transportation and simulation science communities.

EXPERIMENTAL DESIGN AND METHODOLOGY

To analyze the positive (navigational benefit) and negative (distraction potential) impacts of proposed SSS, we implemented a high-fidelity simulator to evaluate human driving performance. These facilities have previously been implemented for applications in safety research, education, and training (Hulme et al., 2021a, 2021b).

High-fidelity driving simulator

The simRING simulator (see Figure 3) is anchored by an electric six degree-of-freedom motion platform. The passenger cabin includes a full front vehicle console with navigation controls (i.e., steering wheel, accelerator, and brake pedals | see Figure 4), a stereo sound system, and a display system that enables an immersive 360-degree field-of-view with a cumulative resolution of 11520 x 1080p.

Figure 3 - simRING (*operator view*)

Figure 4 - simRING (*driver POV*)

Figure 5 – Unity environment

The Unity game engine has been implemented within our simulation framework to create a 10-square mile testing region. EasyRoads 3D and Simple Traffic System were used to configure routes, lanes, and basic traffic logic. Realistic Car Controller uses C# scripting to customize individual vehicle behavior (e.g., tires, suspension, stability). Vehicle inputs (e.g., steering, gas, brake) and calculated vehicle states (e.g., position, speed, acceleration) are implemented for motion cueing. Excursion data is stored for the subject vehicle, the lead vehicle, and environment geometry (e.g., coordinate positions of SSS, traffic signs, exit ramps) for post-processing. The resulting test environment, whose design aspects were previously described in (Hulme et al., 2022), is shown in Figure 5.

Simulated driving scenarios and experimental design

Safe driving involves continuous coordination between visual, mechanical, and cognitive task demands (CDC, 2022). To simulate driver distractions, a car-following paradigm is often adopted, where a "lead vehicle" (e.g., Sena et al., 2016 | see Figure 6) is programmed to brake suddenly to enable measurement of alertness, engagement, and arousal of the "subject vehicle" driver. In our implementation, the lead-vehicle approach was used with a braking event integrated - both at baseline, and within the region of the SSS interaction for comparison.

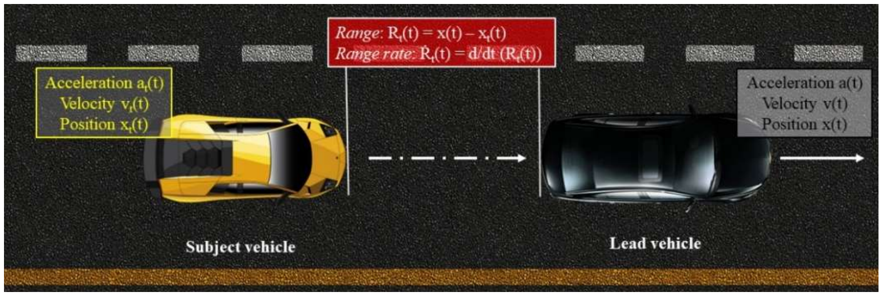

Figure 6 – Lead vehicle approach for simulator distraction analysis

After a brief "acclimation" excursion (Ronen & Yair, 2013), participants took part in two experimental drives: one with reduced information ("Low density"), and one with enhanced information ("High density"). Driver behavior was observed within four "zones of interest" (Z1-Z4): Z1: baseline, Z2: dummy SSS, Z3: dummy slowdown event, and Z4: slowdown event with SSS. Refer to Figure 7, which illustrates our experimental design (the subject vehicle is *shown in purple*). Compared to High density (top of figure), Low density (bottom of figure) has reduced traffic vehicles (*shown in orange*) and reduced "traditional" roadway signs (*shown in yellow*); both by a factor of approximately one-half. Both densities have two slowdown events involving the lead vehicle (*shown in red*), a "dummy" SSS (*shown in green*), and the proposed SSS that is being evaluated (*shown in blue*).

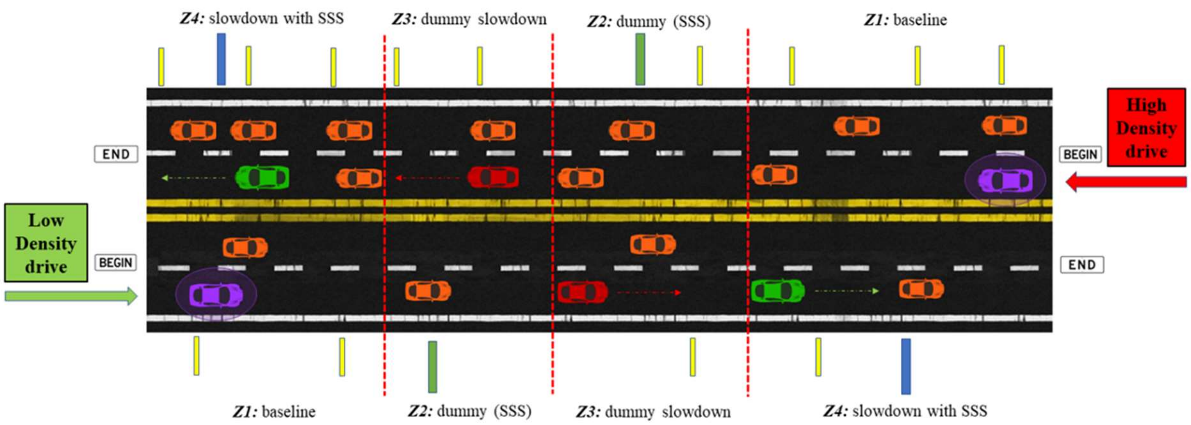

Figure 7 – Experimental Design: Low- and High-density drives (*notional*)

Participants were randomly assigned to either the "Exploratory" (EX) or the "Destination-specific" (DS) sub-cohort. The experimental environments were the same (i.e., Low- and High-density; randomized order), but driver instructions differed accordingly. EX instructions encouraged more navigational freedom, while DS guided direction towards an explicit destination. Our preliminary hypothesis was that drivers that are searching for a specific destination could be more prone to cognitive distraction from the content of a proposed SSS than those who are more casually searching for general places of interest within a region. Refer to Table 1.

Table 1 – Decomposition of experimental sub-cohorts and drive tasks

Cohort sub-groups	Drive Number	Driver Instructions (*Randomized order for DS*)	Information density (*randomized order*)
Exploratory (EX)	1	*For this drive, imagine that you are driving on the highway and are looking for interesting places to visit.*	Low density drive
	2		High density drive
Destination-specific (DS)	1	*For this drive, imagine yourself on a road trip and you are looking for something to do in* ***{destination 1}****.*	Low density drive
	2	*For this drive, imagine yourself on a road trip and you are looking for activities in* ***{destination 2}.***	High density drive

Static/Dynamic Signs survey

The Static/Dynamic Signs survey was issued post-experiment (using Google Forms) for assessment of navigational benefit vs. distraction potential with relation to the proposed SSS. The survey was advised by published literature aimed to evaluate signage visibility (Garvey & Kuhn, 2004). The first (static) segment (see Figure 8) implemented a manufactured artificial roadway sign to acclimate participants towards attributes upon which elaboration is requested.

Potential noteworthy attributes during practice segment:
- Background color of sign
- Border color of sign
- Number of logograms
- Color(s) in logograms
- Color of signage text
- Content of signage text (header/footer)
- Basic shape of sign (e.g., geometry; aspect ratio)

Figure 8 – Static Signs survey (*practice segment*)

The second (dynamic) segment presented the proposed SSS (**re: Figure 2**) within successive animations ranging from 1 to 5 seconds, designed to mimic "glance" durations that might be encountered at different travel speeds (i.e., a brief glance duration for higher speeds; a prolonged glance duration for slower speeds). The goal was to measure the threshold whereby the SSS could be adequately interpreted while driving by. After watching each video, participants were asked to document features and attributes that they were able to observe. The proposed SSS has four logograms (Logogram #1 – Logogram #4) labelled in the sequence in which they physically appear on the sign (i.e., left to right).

Simulator Maladaptation survey

The Motion Sickness Assessment Questionnaire (MSAQ) (Gianaros et al., 2001) was issued to categorize any adverse impacts (e.g., maladaptation) of the simulator experiment. The MSAQ is decomposed into four sub-categories of sickness symptoms; gastrointestinal (i.e., stomach), central (i.e., nervous system), peripheral (i.e., eyes/ears/skin), and sopite (i.e., sleepiness), which are then tabulated into a 0-100% "sickness" rating.

MODELING METHODS

In this section, we provide an overview of our primary modeling methods. These include a modeling methodology for rating safe driver performance, as well as the associated statistical approaches for estimating the impact of the safety rating upon other potentially noteworthy self-rated participant characteristics.

Modeling driving safety performance

We developed a scoring model to quantify driver performance during simulated driving tasks. The Safety Rating (SR) model is defined in Equation (1) and accompanying Table 2.

$$SR = (W_{TS} \times TS) + (W_{TD} \times TD) + (W_{LD} \times LD) + (W_{BE} \times BE) + (W_{BA} \times BA) + (W_{BD} \times BD) \tag{1}$$

Table 2 – Score components for driver Safety Rating (SR) model

Symbol	Score component	Units	Rationale for score subcomponent	Weight
TS	Travel speed	(mph)	Travel proximal to average observed speeds	30%
TD	Speed deviation	(mph)	Maintain constant travel speed	20%
LD	Lateral lane deviation	(feet)	Maintain lane-centric behaviors	20%
BE	Braking events	(count)	Total amount of braking applied	5%
BA	Braking severity	(%)	Harshness of applied braking events	15%
BD	Braking consistency	(%)	Braking uniformity across slow-down events	10%
	TOTAL			**100%**

Note that the weightings (W) selected for the SR model are user-defined and sum to 100% across the six model categories. The values of the ratings (i.e., TS, TD, LD, BE, BA, AS) are calculated from a normal distribution of aggregated driver performance across the entire experimental cohort. Each category rating ranges from a maximum of 1 (i.e., values near the mean cohort value, μ) to a minimum of 0 (i.e., values that are multiple standard deviations σ from the cohort mean). The SR model cumulatively scores each participant on a 0-100 scale.

Modeling approaches for data analysis

The safety rating is modeled using a random parameter ordinary least square regression with heterogeneity in means, which allows a model parameter to vary across observations, and supplies additional information regarding how other (unobserved) factors might impact mean values (Washington et al., 2020). The Pearson (2008) correlation coefficient was also introduced as a normalized measurement of the covariance between variables.

EXPERIMENTAL COHORT

In this section, we describe our study cohort and experimental procedures for our IRB-approved protocol. Likewise, we outline our taxonomy for data collection and analysis.

Experimental cohort and procedures

Our Institutional Review Board (IRB) approved study took place between December 2020 and February 2021. Participant recruitment was conducted via email distribution of a digital flyer. Subject eligibility was based on age (i.e., 18-65), valid U.S. licensure, and (self-reported) no/low susceptibility to motion sickness in a simulated driving environment. Approved participants were scheduled for a two-hour experimental session and were compensated with a $40 (Amazon) gift card. COVID-19 safety and health procedures were prioritized in accordance with strict University guidelines. Table 3 summarizes the full experimental task list.

Table 3 – Experimental Task List

Task order	Activity Description	Duration (minutes)
1	Screening survey (***completed before arrival***)	0
2	Overview of COVID-19 procedures	5
3	Informed consent	10
4	Experiment overview	5
5	Demographic and experience survey	10
6	Simulator safety debriefing & acclimation drive	10
7	Administer MSAQ – participant evaluation (***OK to proceed****?*)	10
8	Experimental drive #1 (*low/high density; counterbalanced*)	15
9	BREAK	10
10	Experimental drive #2 (*low/high density; counterbalanced*)	15
11	Static/Dynamic signs survey	20
12	Experiment de-brief, participant compensation, departure	10
	TOTAL EXPERIMENT DURATION:	**120**

Data collection

Table 4 outlines our experimental cohort (**N=31 | DS**: 17; **EX**:14), which was predominantly (71%) male. The Table summarizes driver age and experience (*green*) and sensory-related statistics (*light blue)*, which were self-reported at baseline using Likert ratings on a 1 (low) to 5 (high) scale, including mean (μ) and standard deviation (σ) for the highlighted variables. Our cohort tended towards younger and less experienced drivers (i.e., average age of approximately 24 years, with just under 3 years driving experience). Our intention was to recruit across a much wider age spectrum. Due to the unfortunate timing of our study deployment, this plan had to be abandoned due to COVID-19 limitations and sponsor-dictated time constraints. Historically, younger adults tend to be more compliant to simulators (Gálvez-García, 2015); in this aspect, demographic limitations worked in our favor.

Table 4 – Summary of cohort demographics and preferences

Experience and Sensory-related							
Sub-cohort	**N**	**Age (yrs.)**	**Experience (yrs.)**	**Video games**	**Vision**	**Memory**	**Hearing**
DS	17	24.8 (6.6)	2.9 (0.8)	2.5 (1.3)	4.7 (0.5)	4.2 (0.8)	4.2 (0.7)
EX	14	23.8 (4.4)	2.6 (0.8)	3.2 (1.1)	4.6 (0.5)	4.4 (0.8)	4.4 (0.5)

Table 5 summarizes the Indictors and Thresholds for our (binary) regression model, classified as: i) socio-demographic and ii) driving opinions and preferences, where the variables included were all identified as being statistically significant in the estimated models.

Table 5 – Indicators for regression model

Socio-demographic			
Indicator	**Binary Threshold**	**μ**	**σ**
Professional	1: if education is an Associate's degree | 0: if otherwise	0.26	0.45
Gender	1: if female | 0: if otherwise	0.29	0.46
Age	1: if between 18 and 24 (inclusive) | 0: if otherwise	0.65	0.49
Driving opinions and Preferences			
Indicator	**Binary Threshold**	**μ**	**σ**
Distraction	1: if daydreaming while driving is perceived as distracting | 0: if otherwise	0.26	0.44
Conversation	1: if frequently converses with passengers while driving | 0: if otherwise	0.45	0.51
Phone Use	1: if occupants use phones for conversations while driving | 0: if otherwise	0.23	0.43
Accomplishment	1: if driver felt fulfilled with the assigned driving tasks | 0: if otherwise	0.87	0.34

RESULTS AND DISCUSSION

In this section, we decompose the presentation of our results into various categories. These include quantitative performance derived directly from our SR model; statistical interrelationships determined from the linear regression and Pearson correlation approaches; self-report findings from the static/dynamic signs segment; and lastly, a brief statement related to observed simulator maladaptation.

Quantitative performance (Driving Simulator)

Various data were collected to determine impacts (i.e., ***navigation versus distraction***) associated with the proposed SSS during the assigned driving tasks. Figure 9 presents the Safety Rating (SR) calculations for each of the two sub-cohorts (i.e., DS, and EX) across the two drive densities (i.e., low, and high) for the entire drive sequence. It is anticipated that SR scores would reduce when comparing low to high density drives. This prediction is based on the increased cognitive load and therefore increased potential for distraction within high density environments. A minor reduction was observed for the DS sub-cohort; however, a slight increase was observed for the EX sub-cohort, while observed variances increased for both sub-cohorts. By way of comparison, Figure 10 targets performance data specifically for Zone 4, our primary region of interest. As expected, SR scores reduced, due to heightened cognitive workload induced by the lead vehicle and increased SSS glance behaviors during information scanning. Observed variances were larger for both DS sub-cohort drives, but smaller for both EX sub-cohort drives.

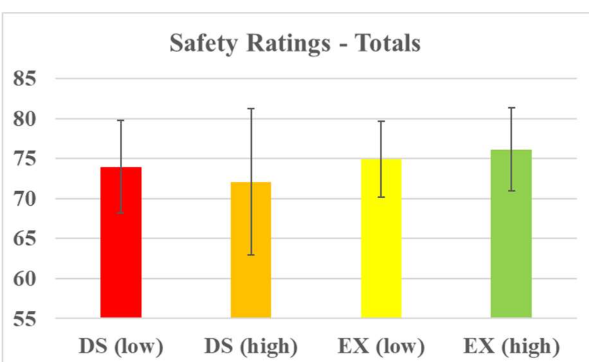

Figure 9 – SR total scores

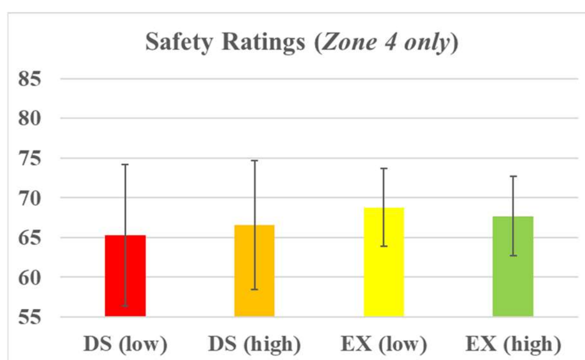

Figure 10 – SR (*Zone 4 only*)

From these plots, our preliminary hypothesis is confirmed: per the SR model, DS sub-cohort subjects were measured to be slightly more distractable (i.e., searching for an explicit destination) than members of the EX sub-cohort (i.e., searching for points of interest without a target destination).

Random parameter linear regression analyses

Noteworthy model estimation results for the key covariates are summarized in Table 6. Note that random parameters are assumed to be normally distributed while modeling. The Constant term (*top of Table*) defines the baseline of driving performance as 68.4 and 73.8 for High Density (HD) and Low Density (LD), respectively, which implies reduced driving performance for the HD condition, as expected.

Under the HD drive condition, females are more likely to exhibit a reduced SR (i.e., 96.8% negative parameters), but *young* females (18-24, inclusive), per the heterogeneity in means model results, can potentially improve their safety ratings by 3.9%. This observation could suggest that females are more easily overwhelmed by the proposed SSS; supported by gender-based perceptions where females are often at elevated risk due to elevated emotional awareness and stress during vehicle operation (Hulse et al., 2018). Also under the HD drive condition, those self-reported with an Associate's degree were identified to have an elevated propensity for a reduced SR (i.e., 86.8% negative parameters), which can potentially be attributed to a variety of underlying factors.

Participants who perceive successful task accomplishment were more likely to garner elevated safety ratings (i.e., 98.3% positive parameters). This might be because overall driving satisfaction has a positive effect on proactive driving behavior, which in turn can positively influence safety perceptions and increased driver performance (Jiang et al., 2021). Within the HD drive condition, the unobserved heterogeneity in means (3.0%) suggests that drivers who frequently converse with live passengers can achieve an elevated SR. This observation could be attributed to a younger cohort being more capable of handling multitasking and complex information flow (Wechsler et al., 2018). However, drivers who prefer using their phone for conversations achieved a reduced SR (-4.9%), even though they felt successful about their own driving. This observation is confirmatory of previous observations that younger drivers often exhibit riskier behaviors coupled with an elevated perception of their driving performance (Barr et al., 2014).

The model further suggests that drivers are more likely to attain a reduced SR if they perceive distraction while driving as being highly distracting (i.e., 87.3% negative parameters), but this trend was observed only within the LD scenario. This could imply that the LD scenario is more likely to result in mindlessness/daydreaming/being "lost in thought," where the sudden presence of the proposed SSS might induce spontaneous distraction and impede driving performance. Note that under the LD drive condition, driver characteristics (e.g., gender, age) did not impart significant influence on the SR, implying that in less strenuous drive conditions, the proposed SSS has the potential to deliver information to drivers (i.e., regardless of demographic characteristics) without impairing behaviors.

Table 6 – Linear Model Estimation Results

Variable/indicator	**High-density (HD)**		**Low-density (LD)**	
	coefficient	*t-stat*	*coefficient*	*t-stat*
Constant term (***y-intercept***)	68.4	50.3	73.8	64.1
Heterogeneity in Means				
	coefficient	*t-stat*	*coefficient*	*t-stat*
Gender & Age	3.9%	2.6	n/a	n/a
Task Accomplishment & Conversation (w/ driving)	3.0%	3.6	n/a	n/a
Task Accomplishment & Phone Use (w/ driving)	-4.9%	-4.7	n/a	n/a
Aggregate distributional effect of random parameters				
	Above 0	**Below 0**	**Above 0**	**Below 0**
Professional (Associate's degree)	13.2%	86.8%	n/a	n/a
Gender (female)	3.2%	96.8%	n/a	n/a
Accomplishment (driving tasks)	98.3%	1.7%	n/a	n/a
Distraction (daydreaming)	n/a	n/a	12.7%	87.3%

Pearson Correlation matrices (Safety Ratings and Demographic data)

We supplemented our statistical analyses with an observation of Pearson correlations between two independent data sources: i) measured simulator performance (**safety ratings | SR**) and ii) self-reported driver characteristics (i.e., as originally reported in Table 4 | *light blue segment*). Figure 11 highlights physiological conditions that reflect participant self-reported sensory capabilities (e.g., vision, memory, and hearing) that are essential for the driving task, as well as self-reported propensity for video games, which could be a general indicator of proficiency in synthetic training environments (Cannon-Bowers & Bowers, 2010), including a driving simulator.

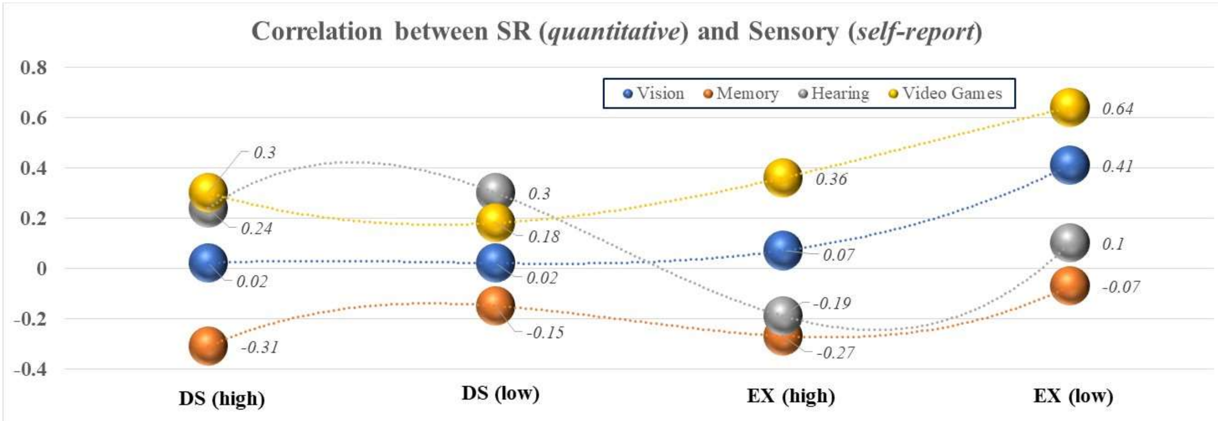

Figure 11 – Data correlates (*physiological*)

Across both sub-cohorts (DS/EX) and drive densities (low/high), there is a positive correlation observed between SR and video game propensity (*yellow series*), which could indicate that frequent video game players are more adaptive to driving simulation. Correlations were stronger for EX than for DS; this could indicate elevated alignment towards "spontaneous" (EX) rather than "directed" (DS) decision-making during roadway navigation. Correlations related to cognition (i.e., memory; *orange series*) for both sub-cohorts were observed to be negative, and more significantly with the high drive-density condition. This could suggest that participants with superior cognitive capability are prone to driving distractibility (i.e., being "lost in thought") regardless of task assignment. Aside from the EX/low condition, Vision (*blue series*) was identified to have a weak positive correlation with SR overall, and for the DS sub-cohort only, Hearing (*gray series*) was observed to have moderately strong positive correlations.

Static/Dynamic Signs segment

Figure 12 documents participant response frequencies related to each logogram of the proposed SSS. According to (NYSDMV, 2018), the **two-second rule** is advised for a suitable "space cushion" towards the road ahead. While contemporary studies (e.g., Oviedo-Trespalacios et al., 2019) remain inconclusive, there is an emerging trend suggesting that roadside advertising can increase crash risk. By these standards, in many situations, it would be unsafe for a participant to gaze at the proposed SSS for two or more seconds. This "Safety Zone" is denoted by a vertical dashed line in the Figure. Separated by this threshold, safe viewing durations (i.e., 1- and 2-seconds) are shaded green (i.e., left side of graph), and danger-prone durations (i.e., 3- and 5-seconds) are shaded red (i.e., right side of graph).

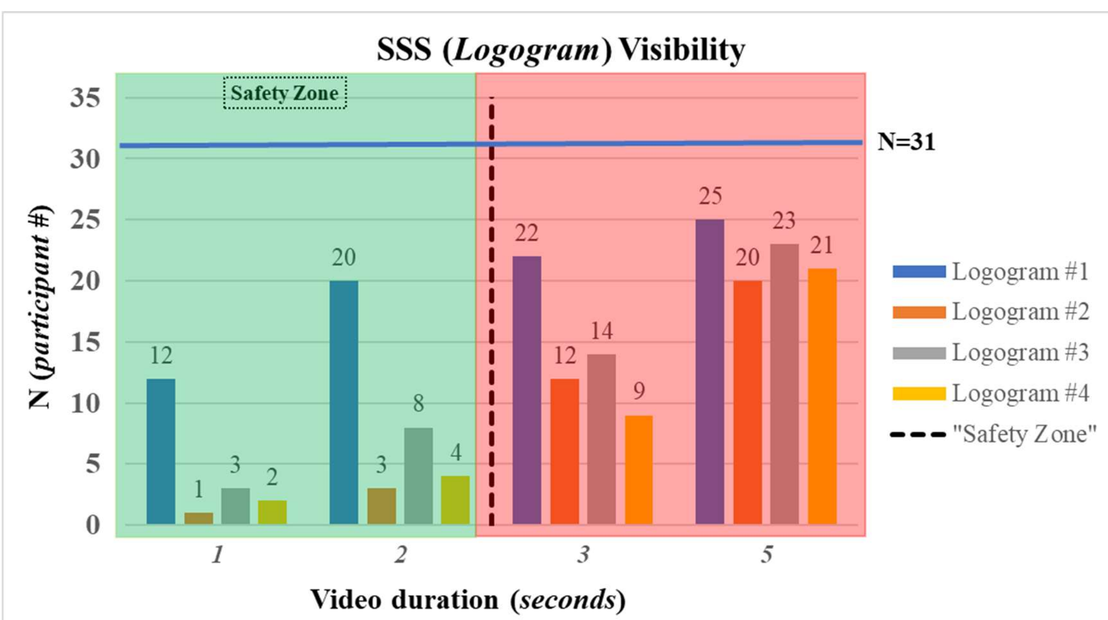

Figure 12 – Dynamic Signs *Glance durations* for proposed SSS

At the longest glance duration (5 seconds), a majority of our study cohort (i.e., as many as twenty-five out of thirty-one, or 80.6%) were able to fully- or partially interpret all four *Logograms*. Observed disparities from one to the next could be related to the positioning of the logograms on the proposed SSS (i.e., drivers are more prone to read from left-to-right), or could be a result of the content/colors of the individual logogram graphics being more noticeable and relatable for a younger study demographic. With a reduced glance duration of 3 seconds, cohort interpretation of all four *Logograms* reduced, ranging from 22/31 (70.9% | *Logogram #1*) down to 9/31 (*Logogram #4*). At glance durations of 2 seconds, only twenty participants (64.5%) explicitly noticed *Logogram #1*, and only eight participants explicitly noticed *Logogram #3*, with greater reductions for *Logograms #2/4*. As expected, these numbers reduce further at the one second glance threshold, where only twelve participants (38.7%) explicitly noticed *Logogram #1*, and many fewer noticed *Logograms #2-4*.

Based on the Dynamic signs segment, Figure 13 displays response frequencies of participants when asked how distracting they found the proposed SSS to be, ranging from 1 (*most distracting*), to 5 (*least distracting*). The cohort consensus (μ=3.12/5; σ=1.35) was that ***the proposed SSS was minimally distracting***. Figure 14 displays the response frequencies of participants when asked how useful (beneficial) they found the proposed SSS to be towards successful navigation, ranging from 1 (*least helpful*), to 5 (*most helpful*). For this query (μ=2.54/5; σ=1.47), the cohort consensus reported ***the proposed SSS was slightly less than beneficial*** towards roadway navigation.

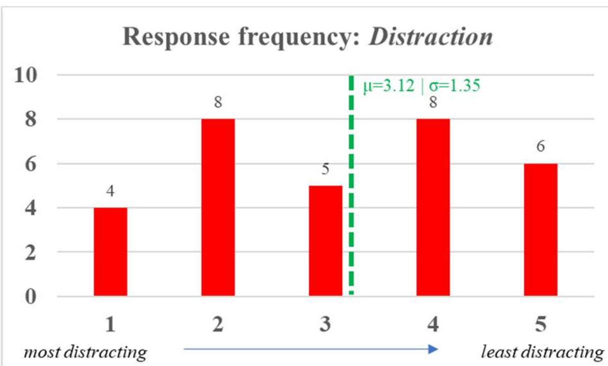

Figure 13 – SSS *Distractibility*

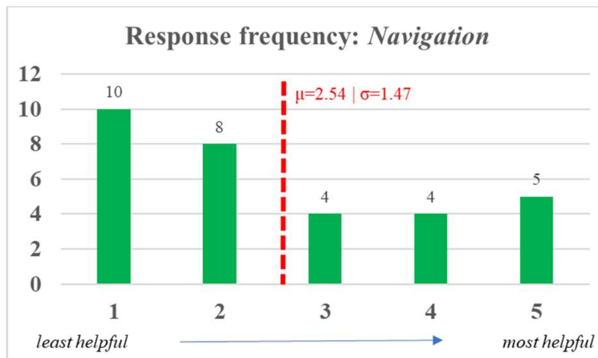

Figure 14 – SSS *Usefulness*

Simulator sickness survey

Figure 15 presents findings related to the MSAQ, with the overall sickness score (0-100) (*red*), as well as the four subcategory ratings (*green*), as percentages. Sickness-related symptoms (μ=2.66% | σ=3.82) were not significant, indicating elevated tolerance to the simulator. Category variances were comparatively high across the entire cohort, as (N=14, or 45.1%) reported no adverse symptoms at all, while the remainder of the cohort (N=17, or 54.9%) reported some sickness symptoms. These observations are not unexpected, as younger adults tend to have elevated tolerance for artificial environments (Keshavarz et al., 2018).

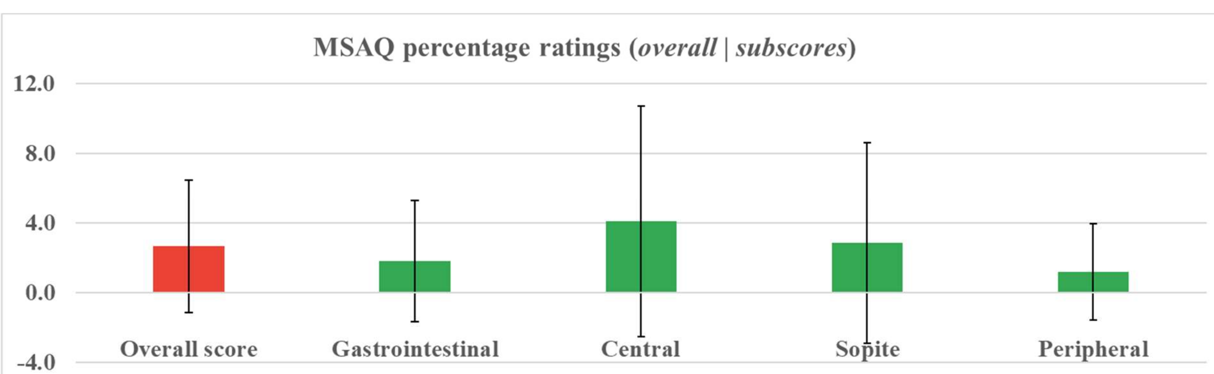

Figure 15 – MSAQ ratings

CONCLUSIONS AND FUTURE WORK

Our primary objective was to employ high-fidelity simulation to evaluate driver performance related to general safety (i.e., ***distraction potential vs. navigational benefit***) from driving interactions with a proposed Specific Service Sign (SSS). Participants were randomly assigned to one of two sub-cohorts that defined their drive tasks: Exploratory (EX) or Destination-specific (DS), across two drives with varying information density (i.e., "low" and "high") within the simulated driving environment. A Safety Rating (SR) model was developed to quantify driver tendencies related to the proposed SSS. Degraded performance was moderately observed in DS related to EX drivers, which may indicate that members of the DS sub-cohort were more distracted (i.e., searching for an explicit destination) than members of the EX sub-cohort (i.e., environment scanning without target destination).

From the linear regression analyses, deeper insights were gained. Increasing environment density in the vicinity of a proposed SSS has the potential to impair safe driving performance. Regarding gender, females were observed to be more vulnerable to high density environments. The proposed SSS should therefore be simplified to reduce any gender disparity due to enhanced cognitive workload. Finally, drivers (and particularly those prone to risky driving habits) might require further education to enable them to capture information from the proposed SSS more safely and timely. Positive Pearson correlations were observed between safety rating and video game proficiency, which could indicate natural adaptivity towards driving simulation among frequent gamers. Negative correlations were observed between SR and memory, which confirms findings from the linear regression analyses -- participants with superior cognitive capability are more likely to be frequently daydreaming (i.e., lost in thought) during a navigation task, and thus more distractable by the SSS. A proposed SSS should therefore deliver information effectively to make drivers confident in their navigation choices to promote safe driving.

Our supplementary Dynamic signs segment indicated that most drivers required 3-5 seconds to safely interpret the proposed SSS navigational attributes which exceed the accepted "2 second rule" guideline for safe following distance. Furthermore, the proposed SSS was rated as being low-moderate in terms of distraction potential but was also rated as being slightly below average in terms of navigation usefulness. Finally, simulator sickness was rated as not significant among our cohort.

Our primary findings illuminate how drivers interact with service signs and the subsequent impact on their performance. Extensions of the current work are underway with a particular focus on the physiological implications of our findings. Electrodermal Activity (EDA) measures electrical changes when cognitive workload increases, and Photoplethysmography (PPG) measures oximetry, from which heart rate variability can be derived (Seitz et al., 2012). Likewise, recent advancements associated with eye tracking enable an improved understanding of visual and thought processes (Li et al., 2021) and provide deeper insights into real-time human driving behaviors (Brunyé et al., 2019). Key correlates from these datasets will be analyzed and reported in a follow-up to the present dissemination. Lastly, while our investigation focused on the SSS, we recommend that future studies consider evaluating the effects of other roadway signs, traffic control devices, and driver information systems.

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