Multi-Modal Evaluation of Adaptive Interface Design and Railway Grade Crossing Infrastructure, in Simulated Driving Environments

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Abstract: This study examines the usability and cognitive workload associated with two interface concepts – Context-Driven Adaptive Dashboard System and a Bring-Your-Own-Device (BYOD) graphical interface – tested within a high-fidelity driving simulator across urban and rural routes. Nineteen participants completed realistic driving scenarios, during which physiological, behavioral, and subjective data were collected. Usability was assessed using the System Usability Scale, while mental workload was measured with the NASA Task Load Index. The results show that the context-aware interface achieved a 20.9% higher usability score compared to a Bring-Your-Own-Device interface (71.7 vs. 59.3, $p = 0.0105$). However, workload levels did not differ significantly across the interfaces. The experiment also analyzed driver behavior at both secured and unsecured railway grade crossings using eye-tracking technology. Eye-tracking analysis revealed unsecured crossings elicited 30.2% more fixations, a 13.8% increase in fixation frequency, and a 26.4% decrease in average fixation duration ($p < 0.01$), reflecting elevated visual search activity and uncertainty. While statistical comparisons of driver risk behavior at crossings yielded limited significance, observed trends consistently pointed to safer actions at secured crossings. These findings underscore the importance of adaptive interface design and intelligent infrastructure in reducing driver distraction and enhancing safety in both everyday and critical driving situations.

Keywords: user interface; driving simulator; railway crossing; eye-tracking

1 Introduction

The development of driver assistance systems in vehicles introduces new challenges in designing Human-Machine Interfaces (HMI). In future vehicles, maintaining driver attention and minimizing distraction is of critical importance, especially in increasingly complex driving environments. One key area of technology development aimed at improving traffic safety is the creation of new, context-driven dashboard interfaces. These systems are designed to alert drivers to the most critical information, thereby reducing the risk of accidents.

This research aims to simplify in-vehicle user interfaces (UIs) with a focus on ergonomics, user experience (UX), and traffic safety. The proposed system, Context-Driven Adaptive Dashboard System (ConDash), adapts to driving conditions to support drivers while reducing cognitive load and distraction. Beyond interface evaluation, the study examined driver behavior at secured and unsecured at-grade railway crossings. These were included in the simulation to assess how interface design affects driver attention and decision-making in critical situations. Subjective measures, including perceived workload and satisfaction, were evaluated to assess interface usability. Eye-tracking technology was also used at grade crossings to record gaze metrics and visual attention.

The structure of our paper begins with a review of existing literature and identifying a research gap. Next, section three covers the measurement method and process, including the metrics used. Section four presents detailed results along with a summary of outcomes. Section five is a discussion, followed by the conclusion and abbreviations.

2 Literature Review

Developing advanced, context-aware dashboard systems requires a comprehensive understanding of both user interface design and driver distraction. Driver distractions – particularly those arising within the vehicle – remain a significant challenge to road safety. These include both technology-based and non-technology-based distractions that affect the driver's cognitive resources [1]. Building upon this, the design and usability of in-vehicle information systems (IVIS) play a crucial role in mitigating such distractions. As vehicle systems grow increasingly complex, adapting the user interface to the driver's context – such as speed, location, or road conditions – becomes essential for enhancing usability and safety. One study emphasizes that drivers prefer adaptive displays over manual interaction mechanisms, reinforcing the importance of intuitive, context-aware design [2]. HMIs were developed to ensure proper interaction between the vehicle and driver. HMIs in vehicles (road and railway) consist of output and input channels.

The output channels provide the operator with information regarding the system status, including visual displays and auditory signals, as well as details on energy consumption and energy-saving functions, utilizing an advanced monitoring and assistance system designed for train operators [3]. Conversely, the input channels accept the operator's intentions to input information, such as through buttons, steering wheels, or pedals [4].

In support of these findings, a multimodal interface was introduced that integrates speech recognition, hand gesture recognition, and rotary control to improve user interaction with infotainment systems [5]. The significance of usability was further confirmed in a study examining the design of touchscreen interfaces. The results showed that medium-to-large square buttons offered optimal performance, demonstrating how interface elements, such as size, shape, and spacing, influence usability and cognitive load [6]. These findings align with earlier research that identified layout clarity, color precision, and rich interaction as key to effective digital dashboard design [7].

The driving context also affects how users engage with IVIS. A study using a fixed-base simulator revealed that subjective workload and secondary task performance vary significantly depending on driving scenarios and task types, indicating the need for adaptable systems that respond to situational demands [8]. In our previous study, a comparison of touchscreens and physical buttons showed that touchscreens led to significantly more visual, manual, and cognitive distractions, as measured by eye-tracking and psychological surveys [9].

Broader analyses of interactive automotive UIs further highlight the shift toward novel modalities such as virtual touch, wearables, speech control, and gaze-based systems. These emerging technologies each offer specific advantages and limitations that must be carefully evaluated when designing automotive interfaces [10]. Smartphone use while driving is another pervasive source of distraction. To address this, researchers proposed a context-aware adaptive UI framework explicitly designed to reduce smartphone-induced distractions while maintaining usability [11]. This represents a targeted application of adaptive technology to improve road safety directly.

Context-aware adaptations have also been explored in terms of how vehicle functions should respond to environmental changes. A layered context model was developed to control automotive functions based on real-time conditions dynamically, utilizing qualitative modeling to simplify complex data inputs from sensors, navigation systems, and camera systems [12]. These contextual attributes serve as the foundation for creating interfaces that are more intuitive and responsive, as our previous work showed the framework of the Dynamic Human-Computer Interface System (DHCIS) [13].

Functionality in such systems is generally divided into Driving-Related Tasks (DRT) and Non-Driving Related Tasks (NDRT), a classification commonly used in human-computer interaction for vehicles. These categories allow for prioritizing safety-critical functions over comfort or entertainment features during high-demand driving conditions [14] [15].

Recent research has extensively applied eye-tracking technology to understand driver attention at railway-level crossings in both simulated and real environments. A simulator study tested six different railway warning systems and found that active visual and audio signals significantly improved driver gaze behavior and compliance compared to passive signage [16]. Participants were more likely to fixate on warning elements and approach the crossing with increased caution, indicating that active measures promote more consistent scanning patterns.

A larger-scale simulator experiment involving 58 participants evaluated the effects of three intelligent transport system (ITS) interventions – roadside signs, in-vehicle visual displays, and auditory alerts – on cognitive load and visual attention [17]. The study concluded that none of the systems caused cognitive overload, and drivers maintained adequate gaze focus across all scenarios. This supports the integration of in-vehicle technologies without compromising safety or increasing mental workload.

In contrast, a real-world field study examined gaze behavior at two types of grade crossings and found that although most drivers glanced at the signage or protection system, nearly 66% failed to look down the tracks, especially when passive controls were in place [18]. This finding reveals a potentially hazardous gap in driver behavior that may not be apparent without eye-tracking data, underscoring the need for improved design or training at passive crossings.

A similar concern was reflected in a simulator-based experiment analyzing eye-movement patterns across varying crossing types. Results showed that active signals significantly increased fixation on relevant areas such as warning devices and trains, while passive crossings resulted in more scattered attention and a higher chance of critical visual omissions [19].

Finally, the accuracy of simulator-based gaze analysis was validated in a study comparing eye-tracking data from simulated and real-world urban driving [20]. Their results confirmed that simulators can reliably replicate real attention patterns, thereby supporting the credibility of simulation-based research in transportation safety.

Enhancing transport efficiency and safety increasingly relies on integrating advanced technologies, whether in railway operations or supply chain management. At railway crossings, automated barriers, signaling, and surveillance systems combined with risk-based assessments can mitigate human error [21]. Similarly, optimizing track alignments using geodetic methods and computer modeling enhances safety, reduces costs, and facilitates standardization for high-speed rail [22]. In logistics, integrating vendor-managed inventory with vehicle routing through heuristic optimization achieves comparable benefits by lowering costs and improving reliability [23].

As a non-invasive and increasingly reliable method for analyzing visual attention and distraction, eye-tracking provides detailed insights into driver behavior by capturing fixation, gaze patterns, and pupil dynamics. Eye movement data, including fixation frequency, pupil diameter, saccades, and blink rate, have been shown to correlate with cognitive load and can indicate varying levels of driver distraction [24] [25]. Fixation behavior, specifically the Point of Regard (POR), is used to define Areas of Interest (AOI) within the vehicle cabin, such as instrument clusters or infotainment systems, to determine how long and how often drivers divert their attention from the road [26].

To complement objective eye-tracking data, the NASA Task Load Index (NASA-TLX) is employed to assess subjective workload. This multi-dimensional tool evaluates six components of cognitive strain: Mental Demand, Physical Demand, Temporal Demand, Performance, Effort, and Frustration Level [27]. Its applicability in naturalistic driving scenarios has been validated due to its sensitivity to mental workload variations and its suitability for non-expert participants [28]. The results from NASA-TLX scores in this study consistently indicated that tasks involving touchscreen interactions imposed a higher mental and physical burden compared to traditional physical interfaces.

The System Usability Scale (SUS), a well-established and quick-to-administer tool, was utilized to measure the perceived usability of the tested interfaces. It provides a global score reflecting the subjective satisfaction with the system's ease of use [29]. The study found a significant disparity between physical controls and touchscreen UIs, with the former receiving high usability scores – indicating intuitive and user-friendly interaction – while the latter was rated significantly lower, reflecting increased complexity and reduced satisfaction during driving.

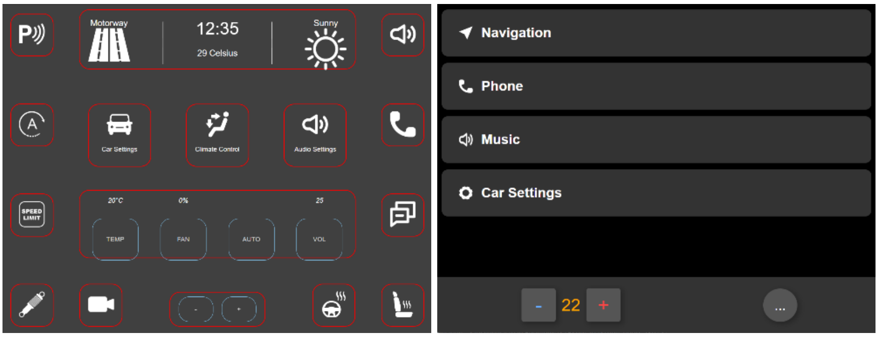
Despite extensive research on adaptive in-vehicle interfaces, little evidence links usability and workload assessments to simplified, context-driven dashboards such as ConDash. At the same time, studies on railway crossings have shown critical shortcomings in driver attention, yet few combine eye-tracking with systematic risk analysis across secured and unsecured crossings. These gaps highlight the need for independent investigations into both adaptive dashboard usability and gaze behavior at railway crossings, providing complementary insights into driver distraction and safety.

3 Measurement Method and Process

The driving simulator experiment was conducted to evaluate two different in-vehicle interface concepts under both urban and rural driving conditions. The test was implemented using the BeamNG driving simulation software, operated on a high-performance simulator hardware setup. The experimental setup consisted of a high-performance desktop PC equipped with an Intel i9 processor and an NVIDIA

GTX graphics processing unit. Visual immersion was provided by three 55-inch OLED monitors arranged in a panoramic configuration. For realistic driving input and feedback, a Moza Racing force-feedback steering base and wheel were utilized, complemented by a set of pedals and a manual shifter. A custom-built dummy dashboard was integrated into the simulator to house a secondary display, which presented real-time gauge readouts and additional interface content. The primary HMI under investigation was displayed on a 12.3-inch tablet PC, mounted in the center console position to replicate an in-vehicle display.

Two distinct interface concepts were evaluated during the study, as shown in Figure 1: ConDash (Interface 1), a context-aware adaptive graphical user interface, and BYOD GUI (Interface 2), a bring-your-own-device-based graphical interface concept [30].



(a) (b)

Figure 1

GUI layout samples: Interface 1 (a) and Interface 2 (b)

As the dynamic interface design of the ConDash system evolved based on DHCIS, multiple context-based functional layout versions were developed to adapt to different driving environments [13]. This study implemented city and rural layout projections, tailored to the specific needs and expectations of drivers in each context. To enhance usability and safety, particular functions were made available as quick-access buttons, dynamically switching based on the environment. These transitions occurred when the vehicle had exited or re-entered an urban area. The functional differences between the city and rural layouts are detailed below:

City layout functions: Parking Aid, Start-Stop, Speed Limiter, Suspension Adjustment, Camera, Air Conditioning, Seat Heating, Source, Phone, Speech Recognition

Rural layout functions: Line Keeping Aid, Windshield Heating / Defogging, Speed Limiter, Drive Modes, Global Positioning System, Air Conditioning, Seat Heating, Speaker (Sound) Settings, Phone, Message

During the simulation, participants drove along rural roads and encountered two types of at-grade railway crossings while interacting with the dashboard interfaces. No additional instructions were provided beyond a navigation prompt stating, “cross the railway”. The first type of crossing was a secured at-grade railway crossing (R1, R2), equipped with barriers, warning signs, and flashing lights. No train was present during the approach or crossing (Figure 2). This type of secured crossing appeared twice within a single simulation round. The second type was an unsecured at-grade railway crossing (R3), marked only by signage, including a STOP sign (Figure 3). Similar to the secured crossings, no train was present at the time of crossing.

Figure 2
Secured at-grade railway crossing equipped with barriers, warning signs, and flashing lights — eye-tracking view of driver (R1, R2)

Figure 3
Unsecured at-grade railway crossing with signage, including a STOP sign — eye-tracking view of driver (R3)

All 19 participants (mean age = 23.42 years, standard deviation = 3.86) wore a Pupil Labs NEON eye-tracking headset, during the sessions [31]. All vehicle dynamics, physiological signals, and simulator events were synchronized and logged in real-time for post-analysis.

3.1 Measurement Process

Participants were welcomed, informed of the study's objectives and procedures, and signed a written informed consent form. Participants were briefed on the basic operation of the simulator and safety protocols. They were asked to behave normally while driving and follow the traffic rules as much as possible. During the familiarization phase, participants first completed a practice drive to become accustomed to the simulator hardware. They then interacted with both interface types in a non-driving context to understand their layout and functionality. Following this, the Pupil Labs NEON eye-tracking headset was applied. Each participant then completed two driving rounds: the first using Interface 1, and the second with Interface 2, both conducted under similar road and task conditions. Throughout each round, a research assistant guided the session using auditory navigation and tasks, following a predefined itinerary on a tablet. UI control secondary tasks were as follows: Increase temperature by 2°C; set fan speed to level 2 or 20%; set climate to AUTO; turn on rear window defroster; turn off rear window defroster; turn on AC; turn on seat heating; turn off seat heating; activate parking assistant; deactivate parking assistant. After completing both rounds, participants filled out a post-drive questionnaire to assess workload, usability, and subjective experience. All collected data were anonymized for subsequent statistical and behavioral analysis. The process steps are shown in Table 1.

Table 1
Measurement Process Steps

Step	Description
Consent & Pre-Test Survey	Informed consent signed
Familiarization	Practice drive and non-driving interface exploration
Sensor Setup	Eye-tracker attached
Test Round 1	Driving with Interface 1, tasks guided by assistant
Test Round 2	Driving with Interface 2, same conditions as first round
Post-Drive Questionnaire	Final survey assessing usability, workload, and preferences

3.2 Measurement Metrics

The UIs were assessed using two widely accepted subjective evaluation tools:

SUS: A 10-item questionnaire providing a composite score from 0 to 100 that reflects perceived usability.

NASA-TLX: A multi-dimensional rating tool capturing mental workload across six subscales: mental demand, physical demand, temporal demand, performance, effort, and frustration. Each participant provided scores on these scales, which were later combined into an overall workload index.

These subjective assessments were complemented by participants' qualitative feedback and interpreted in conjunction with performance and physiological data.

The analysis of infrastructure focusing on grade crossings involved recording participants' gaze behavior during encounters with at-grade railway crossings using Pupil Labs eye-tracking glasses. The study included various eye-tracking metrics, as shown in Table 2.

Table 2
Eye-tracking metrics used in the study

Metric	Unit
Duration of experiment	seconds (s)
Total entries of fixation	count
Fixation frequency	fixations per minute (fix/min)
Mean fixation duration	milliseconds (ms)
Fixation duration SD	milliseconds (ms)
Blink count	count
Blink frequency	blinks per minute (blinks/min)
Blink duration SD	milliseconds (ms)

The Driver Behavior Categorization Framework (DBCF) was developed to assess driver behavior at railroad crossings systematically (Table 3). It divides observed actions into three key behavioral dimensions: speed control, attention to traffic signs (including both signs and lights), and environmental awareness through head or eye movements. Each dimension contains discrete, standardized labels to allow for consistent coding and robust analysis of driving risk patterns across different crossing types.

Table 3
Driver Behavior Categorization Framework

Category	Label	Definition
1. Speed Behavior	Maintains speed	No observable speed reduction
	Reduces speed	Slight or moderate deceleration
	Significantly reduces speed	Noticeable deceleration, possibly preparing to stop
	Comes to a complete stop	Full stop before the crossing or obstacle
2. Sign Attention	No visual engagement	No indication of noticing any sign or light
	Visual engagement	The participant looks at the traffic sign or light
3. Surroundings Awareness	Scans surroundings	Explicit head or eye movements indicating active environmental assessment
	No scanning	No eye or head movements detected

4 Results

Our study results are presented in the subsections detailing the interfaces and railway grade crossings, which include risk assessment and eye-tracking data analysis. The third subsection provides a summary of the results for improved clarity and transparency.

4.1 User Interface Test

The results of the usability evaluation using the SUS indicated that Interface 1 achieved a mean SUS score of 71.7, corresponding to a grade of B (Good). In contrast, Interface 2 received a mean score of 59.3, which equates to a grade of D (Poor) (Figure 4). These scores suggest that participants generally perceived Interface 1 as more usable than Interface 2.

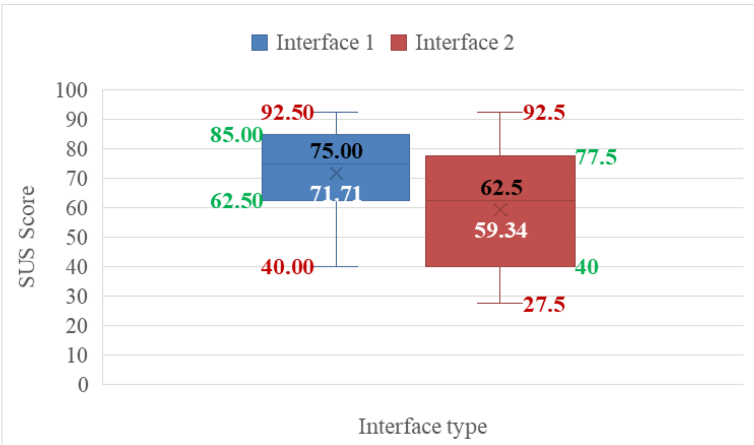


Figure 4

SUS scores by interface, showing mean (white), median (black), quartiles 1 and 3 (green), and standard deviation (red)

To statistically assess this difference, non-parametric tests were employed due to the small sample size and the ordinal nature of the data. The Wilcoxon signed-rank test confirmed a significant difference between the usability ratings of the two interfaces ($W = 15.0$, $p = 0.0105$). Furthermore, a Spearman rank correlation analysis revealed a moderate and statistically significant positive correlation between the SUS scores of the two interfaces ($\rho = 0.59$, $p = 0.0077$), indicating that participants who rated one interface higher tended to rate the other similarly.

The comparison of the two interfaces using the weighted NASA-TLX scores reveals that the distribution of perceived workload is very similar between Interface 1 and

Interface 2. Figure 5 shows nearly identical medians and interquartile ranges across the two conditions.

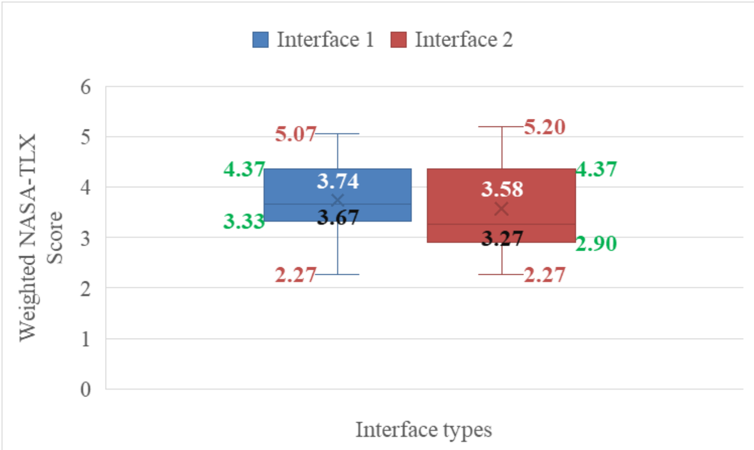


Figure 5
Weighted NASA-TLX scores by interface, showing mean (white), median (black), quartiles 1 and 3 (green), and standard deviation (red)

Statistical analysis using the Wilcoxon signed-rank test resulted in a test statistic of $W = 76.00$ with a p-value of 0.465, indicating that there is no statistically significant difference in perceived workload between the two interfaces. Additionally, a Spearman rank correlation, which assesses the strength of monotonic relationships, yielded a correlation coefficient of $\rho = 0.570$ with a p-value of 0.011. This reflects a moderate and statistically significant positive correlation between the individual scores across interfaces. In other words, participants who rated one interface as more demanding tended to do the same with the other.

4.2 Railway Grade Crossing Analysis

The following subsections present the detailed results of the grade crossings risk assessment, offering an in-depth analysis of driver behavior. The next subsection displays the eye-tracking data analysis results.

4.2.1 Risk Assessment

The analysis aimed to examine how driver behavior varies between secured and unsecured railroad crossings by categorizing actions into risk levels: low, medium, and high. The distribution of these risk levels for two conditions was visualized in Figure 6: crossings equipped with active signals (R1 & R2), and those lacking such infrastructure (R3). The visual evidence immediately highlighted that secured crossings elicited predominantly low-risk behavior – characterized by proper speed management, visual attention to signs, and active scanning of the surroundings. In contrast, the unsecured crossings showed a relatively higher portion of high-risk behaviors, including failures to slow down, to notice traffic signs, or to look around before proceeding.

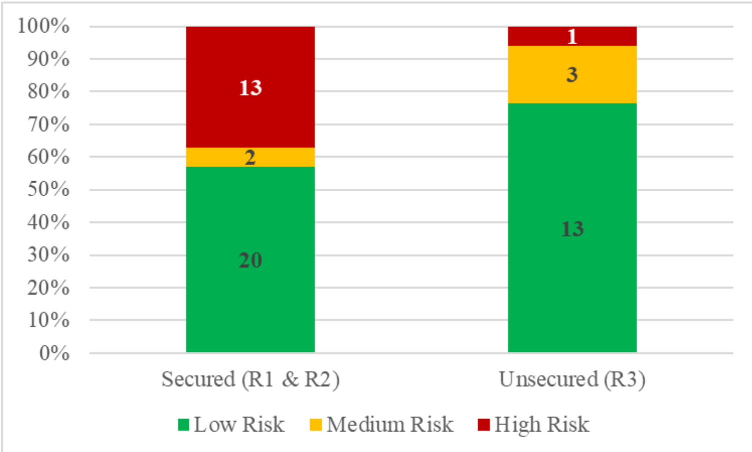


Figure 6
Risk level comparison: secured and unsecured railroad crossings

While initial trends suggested a behavioral safety benefit for signalized crossings, statistical validation was necessary. A chi-square test found no significant difference in risk level distributions between crossing types ($p = 0.4999$), likely due to limited sample size. To avoid distributional assumptions, non-parametric tests were employed. Both the Mann-Whitney U test ($p = 0.7339$) and the Kruskal-Wallis test ($p = 0.7329$) confirmed no significant differences in ranked risk levels. However, the Wilcoxon signed-rank test indicated a significant difference ($p = 0.0339$), suggesting some divergence in relative risk distributions. A Spearman correlation ($\rho = 1.0$, $p < 0.001$) further revealed perfect ordinal agreement, indicating consistent response patterns despite variations in frequency.

4.2.2 Eye-Tracking Data Analysis

This section presents the comparative analysis of eye-tracking metrics recorded in two types of grade crossings. The comparison is based on multiple indicators of visual and cognitive load, including fixation and blink characteristics.

Table 4 summarizes the descriptive statistics of key eye-tracking parameters in both conditions. The total number of fixations was considerably higher in the unsecured condition (M = 32.56, SD = 10.52) than in the secured one (M = 25.00, SD = 8.17). This was reflected in a significantly higher fixation frequency in the unsecured scenario (M = 152.75 fixations/min) compared to the secured one (M = 134.27 fixations/min), with p = 0.006, indicating increased visual search activity in more complex or ambiguous crossing environments.

Table 4
Statistics of selected eye-tracking parameters

	Secured			**Unsecured**		
	Mean	**SD**	**Median**	**Mean**	**SD**	**Median**
Duration of experiment [s]	11.15	2.50	10.52	12.82	3.62	12.52
Total Entries of fixation	25	8.17	27	32.56	10.52	30
Fixation Frequency (fix/min)	134.27	30.95	135.6	152.75	26.88	157.97
Mean Duration of fixation [ms]	506.14	297.38	429.2	372.51	87.81	362.57
Standard Deviation of fixation duration [ms]	462.53	271.27	405.64	291.33	105.58	272.34
Blinks Count	1.94	1.85	1.50	1.89	1.57	2
Blinks Frequency (blinks/min)	9.76	8.67	7.80	8.80	7.12	9.36
Blinks SD (ms)	14.55	14.65	11.47	15.9	22.58	3.54

The total number of fixations was considerably higher in the unsecured condition (M = 32.56, SD = 10.52) than in the secured one (M = 25.00, SD = 8.17). This was reflected in a significantly higher fixation frequency in the unsecured scenario (M = 152.75 fixations/min) compared to the secured one (M = 134.27 fixations/min), with p = 0.006, indicating increased visual search activity in more complex or ambiguous crossing environments.

Moreover, the mean duration of fixation was substantially lower in the unsecured crossing (M = 372.51 ms) than in the secured one (M = 506.14 ms), accompanied by a similar reduction in the standard deviation of fixation durations. These findings suggest that participants may have adopted a more fragmented, scanning-type gaze behavior under the less predictable conditions of the unsecured crossings. Blink-related metrics showed no statistically significant differences.

The Wilcoxon signed-rank test confirmed statistically significant differences in several visual behavior indicators between secured and unsecured grade crossings (Table 5). These results highlight robust behavioral adaptations in gaze allocation patterns when encountering different infrastructure designs. Additionally, the Spearman correlation showed strong positive associations across the two conditions in these metrics. For example, mean fixation duration showed a correlation coefficient of $\rho = 0.678$ ($p = 0.002$), indicating that although the average level differed, the relative ranking of participants remained consistent across scenarios.

Table 5
Statistical analysis results of eye-tracking data

Metric	**Wilcoxon Statistic**	**Wilcoxon p-value**	**Spearman Correlation**	**Spearman p-value**	**Significant (p<0.05)**
Duration of experiment [s]	57	0.2288	0.2714	0.2760	No
Total Entries of fixation	22.5	0.0040	0.5696	0.0136	Yes
Fixation Frequency (fix/min)	24	0.0056	0.5707	0.0134	Yes
Mean Duration of fixation [ms]	14	0.0008	0.6780	0.0020	Yes
Standard Deviation of fixation duration [ms]	9	0.0003	0.5831	0.0111	Yes
Blinks Count	72	0.8301	0.2274	0.3641	No
Blinks Frequency (blinks/min)	66	0.6192	0.3137	0.2050	No
Blinks SD (ms)	64	0.8361	-0.1509	0.5502	No

4.3 Summary of Results

The comparative evaluation revealed several statistically and practically significant findings across the user interface test and the railroad crossing analyses.

Interface 1 outperformed Interface 2 in terms of usability, with a mean SUS score that was 20.9% higher (71.7 vs. 59.3), corresponding to grades B (Good) and D (Poor), respectively. This difference was statistically significant (Wilcoxon W = 15.0, $p = 0.0105$), indicating a clear preference for Interface 1. The SUS scores were also moderately and positively correlated ($\rho = 0.59$, $p = 0.0077$), suggesting consistent subjective evaluation tendencies among participants.

In contrast, perceived workload (NASA-TLX) did not differ significantly between interfaces ($p = 0.465$), although a moderate correlation ($\rho = 0.570$, $p = 0.011$) indicated that participants who perceived one interface as more demanding tended to do so for the other as well.

While visual data suggested safer behavior at secured grade crossings, statistical tests mostly failed to confirm significant differences in DBCF risk level distributions (e.g., chi-square $p = 0.4999$; Mann–Whitney $p = 0.7339$). However, a Wilcoxon signed-rank test ($p = 0.0339$) did indicate a significant difference in risk distribution rankings, and a perfect Spearman correlation ($\rho = 1.0$, $p < 0.001$) suggested strong consistency in risk rank structure between secured and unsecured conditions.

Eye-tracking metrics revealed several robust differences between secured and unsecured crossings. Participants exhibited a 30.2% increase in the number of fixations (M = 32.56 vs. 25.00) and a 13.8% increase in fixation frequency (152.75 vs. 134.27 fix/min) under unsecured conditions, both of which were statistically significant ($p < 0.01$). Simultaneously, the mean fixation duration decreased by 26.4% (372.51 ms vs. 506.14 ms), indicating a shift toward shorter, more fragmented gazes in more ambiguous environments. These changes suggest elevated visual search activity and cognitive load in unsecured crossings.

Blink-related measures, including count and frequency, showed no significant differences across conditions. Spearman correlations for fixation-related metrics ranged from $\rho = 0.569$ to 0.678 (all $p < 0.015$), indicating consistent individual response patterns despite environmental differences.

5 Discussion

The results of the SUS and NASA-TLX assessments reinforce the notion that usability and workload are not only measurable but also stable across different interface types. Previous literature shows that higher SUS scores reflect the established finding that physical controls offer more intuitive interaction, reducing cognitive effort [6] [29]. In our study, the usability of the more focused and intuitive Condash (Interface 1) was comparable to that of the more conventional GUI (Interface 2), even though it would have been a different interface type (e.g., physical buttons instead of a touchscreen). Despite Interface 2 scoring lower overall, the stable within-subject response patterns on both SUS and NASA-TLX suggest that individual perceptions of usability and workload remain reliable and contextually anchored, echoing findings by von Janczewski et al. [28].

These results align with earlier work that highlights the ergonomic superiority of physical interfaces in minimizing cognitive and visual distractions, especially under high-demand driving conditions [9]. While touchscreen interfaces are now ubiquitous, their complexity can elevate both perceived and actual task load – a phenomenon reflected in our participants' workload reports and supported by prior studies on IVIS systems [1].

Behavioral data from grade crossings adds another layer to this analysis. Although statistical tests offered mixed results, visual and categorical trends suggest safer behavior at secured crossings. This partially confirms simulator-based findings by Fakhrhosseini et al., who demonstrated more focused attention and fewer visual omissions in the presence of active signaling [19]. Similarly, our observation of heightened fixation activity at unsecured crossings aligns with theories of increased environmental uncertainty [25]. Drivers likely used more frequent, shorter fixations as a compensatory visual strategy to manage ambiguity.

The lack of blinking differences further supports the idea that some physiological markers (like blink rate) are less sensitive to contextual variability – reinforcing Skaramagkas et al.'s assertion that cognitive demands affect specific oculomotor patterns more than others [25].

From an applied perspective, these results validate the integration of context-sensitive visual control measures, particularly at high-risk intersections. The field study by Grippenkoven et al. demonstrated that drivers frequently overlook critical visual checks when only passive signage is present [18]. In our analysis, the elevated visual attention at unsecured crossings reflected a situational response to increased risk rather than systematic precaution. This highlights the need for simulation-based training environments, where drivers can be prepared in advance to adopt consistent, proactive scanning strategies at railway grade crossings.

The ConDash system plays a crucial role in this context. Its adaptive design, rooted in context-aware UI principles, offers a promising pathway for reducing driver cognitive load without compromising critical task performance [11] [32]. By combining real-time interface adaptation with infrastructure awareness (e.g., detection of an upcoming unsecured crossing), future systems could proactively prompt drivers to adopt safer visual strategies.

Future studies should involve a larger and more diverse participant sample to enhance the statistical power and generalizability of the findings. A more detailed eye-tracking analysis focusing on specific interface elements through Area of Interest (AOI) detection will provide deeper insight into user interaction patterns. Additionally, expanding the range of driving scenarios could help evaluate how adaptive interfaces perform under varied contextual demands.

Conclusions

This study investigated two critical aspects of driving safety: The usability of adaptive in-vehicle interfaces and the behavioral effects of on-grade railway crossing infrastructure, using a multimodal evaluation approach. The context-aware ConDash interface outperformed the BYOD solution in terms of perceived usability, with a 20.9% higher SUS score (71.7 vs. 59.3, $p = 0.0105$), representing a shift from a poor (D) to a good (B) usability rating. Although perceived workload did not differ significantly between the two interfaces ($p = 0.465$), moderate correlations in both SUS and NASA-TLX results ($\rho \approx 0.57$) suggest stable subjective evaluation patterns across conditions. These findings confirm that adaptive interface design can enhance usability without imposing a cognitive burden.

The grade crossing analysis revealed that unsecured crossings induced a 30.2% increase in fixation count and a 13.8% rise in fixation frequency compared to secured crossings ($p < 0.01$), alongside a 26.4% reduction in average fixation duration (372.5 ms vs. 506.1 ms). These shifts indicate a transition to faster, more fragmented gaze behavior under uncertain visual conditions – reflecting elevated visual search demands and cognitive effort. While statistical confirmation of increased behavioral risk at unsecured crossings was limited (e.g., chi-square $p = 0.4999$), the Wilcoxon test ($p = 0.0339$) and perfect rank-order correlation ($\rho = 1.0$, $p < 0.001$) support meaningful structural differences in risk response.

Although the user interface test and railroad crossing analysis were methodologically independent, both underscore how design – whether inside the vehicle or in the road environment – can significantly influence driver attention, cognitive load, and safety-related behavior.

Future systems should integrate adaptive HMI strategies with infrastructure-aware alerts, to better support driver performance in complex or ambiguous traffic scenarios.

Abbreviations

AOI	Area Of Interest
BYOD	Bring-Your-Own-Device
ConDash	Context-Driven Adaptive Dashboard System
DBCF	Driver Behavior Categorization Framework
DHCIS	Dynamic Human-Computer Interface System
DRT	Driving-Related Tasks
HMI	Human-Machine Interfaces
ITS	Intelligent Transport System
IVIS	In-Vehicle Information Systems
NASA-TLX	NASA Task Load Index
NDRT	Non-Driving Related Tasks
SUS	System Usability Scale
UI	User Interfaces
UX	User Experience

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