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Comparative Analysis of Driver Interface Systems in Ultra-Efficient Lightweight Electric Vehicles: a Study on Energy Efficiency and Driver Focus

Viktor Nagy*, István Kecskeméti, Zoltán Pusztai

Széchenyi István Univeristy, Hungary, H9026 Győr, Egyetem Tér 1
nviktor@sze.hu

This paper presents a comprehensive examination of two driver interface systems within the context of Ultra-Efficient Lightweight Electric Vehicles (ULEV) aimed at enhancing energy efficiency and optimizing driver focus. The vehicle employs two interface systems: a 10.1-inch touchscreen tablet with a custom Graphical User interface (GUI) that offers comprehensive data management, diagnostics, and control functionalities and a 5.5-inch wide, passive OLED display designed for ultra-low energy consumption. The tablet's advanced features come with the potential for driver distraction. In contrast, the OLED display takes a minimalist approach by presenting only critical information. This enhances driving focus and efficiency. This research utilizes a wearable eye-tracking device to measure drivers' focus and distraction levels while also logging driving performance and energy consumption data. The aim is to determine the most effective interface for promoting efficient driving practices. The study achieved significant insights into the balancing of information accessibility and cognitive load in driving while also optimizing energy efficiency. The results demonstrate the advantages of assistant systems, which reduce energy consumption by 11-15%, provide concentrated information projection, and minimize driver distraction.

1. Introduction

Global warming poses a growing threat to our daily lives, with transport being a major contributor to greenhouse gas emissions (European Environment Agency, 2016). Over the past decades, passenger cars have become more widely available, but unfortunately, their emissions have only slightly decreased (European Environment Agency, 2023). Although this is a significant increase from previous years, it is still a fraction compared to ICE vehicles, which continue to dominate the market (IEA, 2024). Technological advances are essential to support the electrification of global transport. Our research focuses on ULEV and advanced on-board interfaces, which are key to supporting this transition. By improving the efficiency and user experience of electric vehicles, the aim is to contribute significantly to the sustainable mobility landscape.

1.1 Lightweight electric vehicle

The viability of lightweight electric vehicles (EVs) is supported by several key factors. Lightweighting improves the energy efficiency of EVs by reducing their mass, which decreases power demand and extends the vehicle's range. This is crucial because a lighter vehicle requires less battery power to move, allowing for longer travel distances on a single charge (Stabile et al., 2021). Our previous research on driving strategy optimization describes the vehicle model based on measurements, minimizes inaccuracies, and is combined with an optimization framework using a genetic algorithm. This algorithm optimizes acceleration positions on a track. Considering the specific properties of the vehicle and the given track, a speed profile is created during optimization, which the driver can follow using various methods (Pusztai et al., 2023).
A suboptimal energy management strategy based on Pontryagin’s Minimum Principle (PMP) was developed for fuel-cell hybrid electric vehicles (Song et al., 2020). Additionally, a PMP approach was applied to design an eco-driving strategy for EVs, optimizing energy consumption at urban intersections under varying traffic conditions (Jayson et al., 2024). Similar traffic conditions were examined for connected autonomous vehicles using a hybrid

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reinforcement learning (HRL) framework (Bai et al., 2022). Effective energy reduction was achieved for electric bus rapid transit through velocity curve optimization using NSGA-II (Zhang et al., 2024). Energy-efficient speed control strategies for autonomous vehicles were developed via deep reinforcement learning (Du et al., 2022). While previous work primarily simulated autonomous vehicles, the presented paper introduces a novel approach by integrating state-of-the-art optimization techniques with Human-Machine Interfaces (HMI) and validating results through real-world implementation.
The Shell Eco-marathon is a competition where lightweight vehicles employing cutting-edge technology compete against each other. The primary goal is to achieve the lowest possible consumption while completing the race distance within a specified time frame. This time frame ensures that the constructed race vehicles travel at an average speed of approximately 25 km/h (depending on the race rules), effectively simulating urban traffic conditions. Participants must stop and accelerate during each lap in the Urban Concept category. The SZEnergy team from Széchenyi István University participated in this competition and was the winner of the Urban Concept Battery Electric category in recent years.

1.2 Driver distraction and attention detection

The term "driver distraction" is defined in the literature as "the diversion of attention away from activities critical for safe driving toward a competing activity" (Regan and Hallett, 2011). The estimation of driver inattention can be achieved using eye tracking and appropriate algorithms. A study discusses the extensive use of eye tracking in studying driver attention to provide a deeper understanding of drivers' informational needs and behaviors in different driving situations (Ahlström et al., 2021). Another research addresses the significant issue in eye tracking research regarding the problems in defining Areas of Interest (AOIs) in naturalistic driving scenarios, which provide better measurement possibilities for visual attention (Nagy et al., 2024). An innovative application design for analyzing eye-tracking data using visual analytics (Blickshift Analytics) allows users to efficiently analyze large eye-tracking datasets and identify patterns and correlations between eye movements and other data streams. This design leverages both human visual pattern recognition and computational power to enhance the analysis of complex data sets (Raschke et al., 2016).

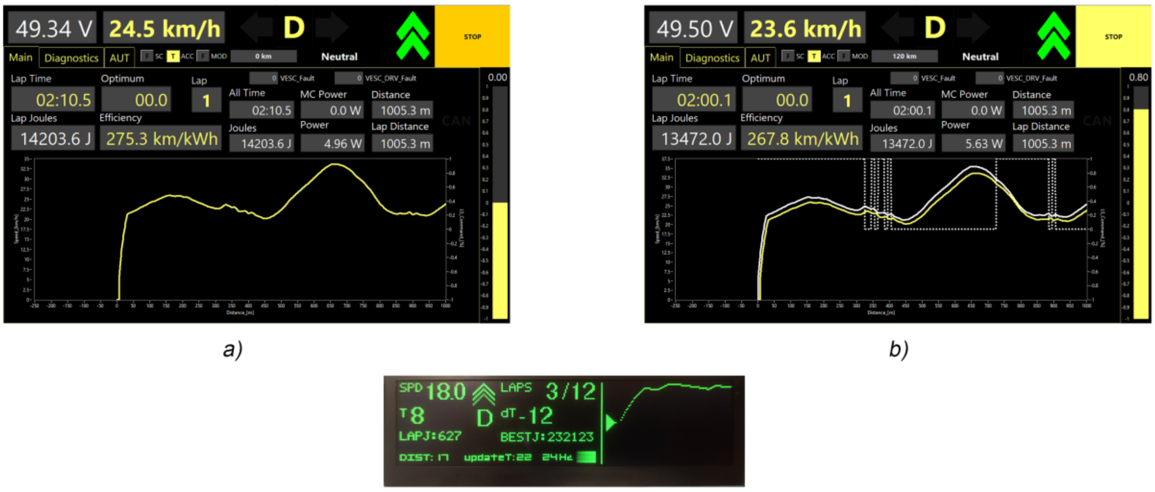
1.3 Interfaces

Human-Machine Interfaces (HMIs) were created to facilitate effective interaction between the vehicle and the driver, so more studies have concentrated on developing efficient Graphical User Interfaces (GUIs) for various process monitoring (Rahim and Ahmad, 2017). The effects of touchscreen size, user interface design, and subtask boundaries was explored on the visual distraction potential of secondary tasks. The findings indicate that larger touch screens slightly reduce in-car glance durations, decreasing visual demand and distraction potential (Grahn and Kujala, 2020). Touchscreen panels in vehicles may enhance dashboard aesthetics, but they can also create significant distractions for drivers (Zulkefli et al., 2022). While touchscreens may work well during stationary moments, tactile controls such as buttons or dials are often more intuitive and safer for use while driving. Also, the usability, benefits, and drawbacks of integrating the Bring-Your-Own-Device concept within In-Vehicle Information Systems (IVIS) were investigated. Results showed that using a mobile phone for IVIS tasks significantly reduced visual distraction and steering intensity compared to a larger tablet interface (Nagy et al., 2023).

2. Test procedure

A test run was conducted on the 576 m long ZalaZONE test track. The aim was to evaluate the effectiveness of three different driving interfaces on an ultralightweight race car. Two professional drivers participated, each completing five laps for each of the three interfaces, totaling 30 laps per driver. The test procedure employed a wearable eye-tracking device, Pupil Neon, to monitor visual attention. The Pupil Neon was chosen due to its demonstrated median accuracy of 1.8° without user-specific calibration and 1.3° with a simple offset correction, as well as its robustness across various lighting conditions and head positions, making it reliable for real-world scenarios (Dierkes & Baumann, 2023). Eye-tracking data were recorded using a mobile companion application, which uploaded the raw data to a cloud service for subsequent post-processing.
The following interfaces were subjected to the testing procedure (Figure 1):

(a) a 10.1-inch tablet displaying vehicle data such as speed, time, and aggregated consumption (Tab);
(b) a 10.1-inch tablet with assistance, which provided a pre-calculated driving strategy for maximum energy efficiency, using the projection of an ideal speed profile (TabAssist); and
(c) a 5.5-inch OLED screen with assistance functionality, which offered focused information for high-efficiency driving and reduced display power consumption (OledAssist).



a) b) c)

Figure 1: Interfaces: a) Tablet layout; b) Tablet with assistance layout; c) OLED screen with assistance layout

During the tests, the pilots first drove without help and followed a distance speed curve displayed on two visual devices. Data were recorded with the help of the vehicle's custom Vehicle Control Unit (VCU), recording the real speed profiles and other metrics. In the first experiment, pilots completed laps without seeing the optimized profile and then used TabAssist to investigate their impact on energy consumption and driving consistency. Data on vehicle performance and visual tracking metrics were continuously recorded for post-test analysis to compare interface effectiveness in driving efficiency and driver participation.

3. Results

3.1 Energy consumption

The quantification of energy consumption was relatively straightforward using the VCU. However, the analysis of consistency required a more in-depth approach. The speed profile recorded by the VCU was interpolated at 2 m intervals along the track length in order to obtain comparable measurement points. Other measured values were also associated with these interpolated speed curves. The interpolated speed curves were analyzed based on the identical distance values covered on the track. Deviations from the ideal speed profile were examined using the following statistical tools:
Mean Absolute Deviation (MAD) shows the average absolute deviation of data from the mean as illustrated in Eq(1). It is a robust measure, less sensitive to outliers compared to standard deviation.

$$MAD = \frac{1}{n}\sum_{i=1}^{n}|x_i - \mu| \tag{1}$$

Root Mean Square Error (RMSE) is the square root of the average squared differences between the data and the estimated values, as Eq(2) shows.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2} \tag{2}$$

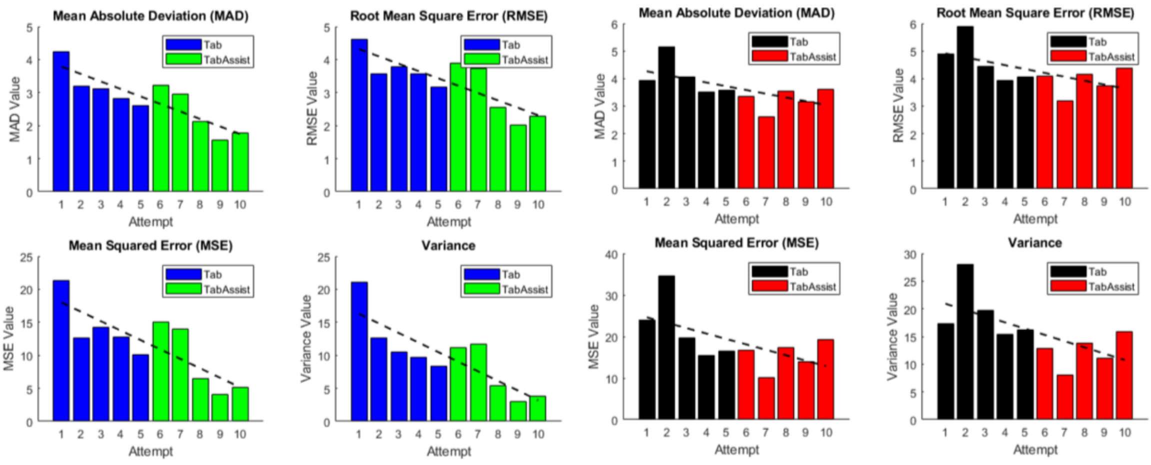
Mean Squared Error (MSE) is the average of the squared differences between the data and the estimated values as seen on Eq(3).

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(x_i - \hat{x}_i)^2 \tag{3}$$

In statistics, variance is a measure of the dispersion of data points around the mean. A high variance indicates a greater degree of variability, with data points widely dispersed around the mean. Conversely, a low variance indicates less variability, with data points concentrated around the mean. Variance is particularly sensitive to outliers, as squaring the deviations amplifies larger differences. See Eq(4).

$$Variance = S^2 = \frac{1}{n-1}\sum_{i=1}^{n}(x_i - \mu)^2 \qquad (4)$$

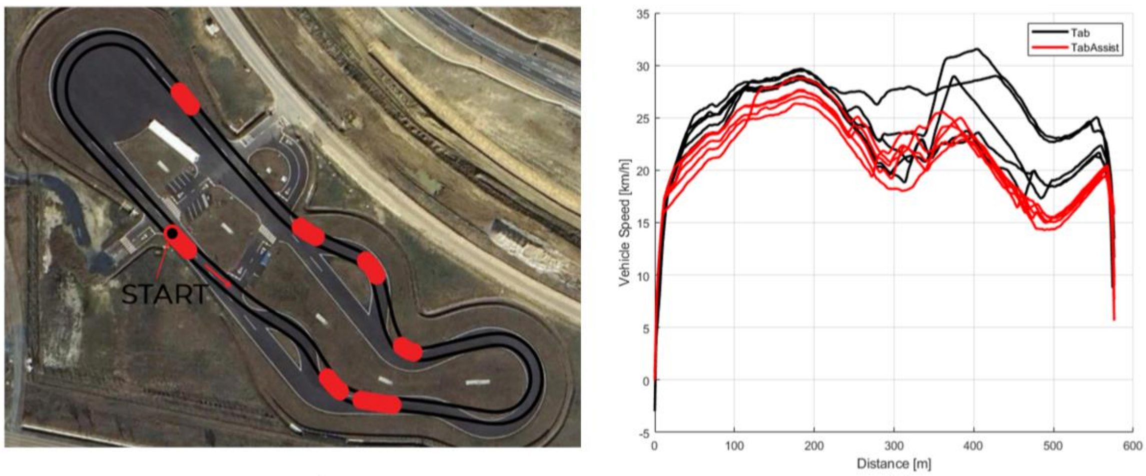
Figure 2 illustrates that for both drivers A and B, the linear trendlines fitted to all four statistical indicators are decreasing. This indicates that the use of the TabAssist display during laps 6-10 helped stabilize driving and made it more consistent. Figure 3 shows the track with red dots indicating the acceleration points that the pilot needed to follow. During acceleration, the driver had to hold down a button that automatically provided the appropriate torque reference.



a) b)

Figure 2: Statistical measures for A (a) and B (b) drivers using Tab and TabAssist

Figure 3a depicts the test track, which is divided into throttle and rolling phases for each lap. In order to achieve optimal energy efficiency, it is necessary to maximize throttle optimization and extend low-resistance rolling sections. The speed profile, shown in Figure 3b, consistently reflects the dynamics of the run, which is crucial for estimating energy efficiency. This profile provides insight into the vehicle's performance during different phases of operation.



a) b)

Figure 3: a) Test track (red bars showing throttle sections); b) Speed profile of B driver with Tab and TabAssist

3.2 Drivers's attention

The post-processed eye-tracking data, which was obtained from Blickshift Analytics, was used in conjunction with dynamic AOI detection to frame the Tab and OLED screens. This allowed for the analysis of driver gaze patterns. Gaze filtering techniques were used to extract key eye-tracking metrics, including the following, as shown in Table 1:

- Normalised Gaze Duration (NGD): The amount of time the driver's gaze is fixed on the specified AOIs (Tab or OLED screens), normalised to account for variation between drivers and sessions.
- Fixation Rate (FR): The frequency with which the driver's gaze is fixed on the AOIs.
- AOI Transition Rate (ATR): The rate at which the driver's gaze moves from one AOI to another.

The addition of the Average Joule/Laptime (J/L) metric, derived from energy consumption data, provides a comprehensive view of each driver's performance and interaction with different user interfaces.

Table 1: Eye-tracking metrics and energy consumption

Driver	User Interface	NGD	FR	ATR	J/L
A	Tab	0.40	79.82	3.93	115.71
B	Tab	0.26	56.68	2.92	130.54
A	TabAssist	0.53	105.57	3.69	112.25
B	TabAssist	0.37	76.17	3.36	96.69
A	OledAssist	0.30	59.87	2.04	117.71
B	OledAssist	0.36	75.09	1.90	102.60

The TabAssist interface was the most engaging for drivers, as indicated by the highest NGD and FRs. Conversely, the OledAssist interface had the lowest ATR, implying fewer distractions. Performance efficiency, as measured by J/L, varied more significantly for Driver B, highlighting potential differences in individual adaptation to interface types. These findings indicate that while TabAssist may capture more attention, OledAssist may offer a less distracting driving experience. A correlation matrix was generated to identify the strength and direction of relationships between different performance metrics, which reveals a strong positive correlation between NGD and FR (0.995), a moderate positive correlation with ATR (0.568), and a moderate negative correlation with Average J/L (-0.394).

4. Conclusion

Our study provides insights into how different user interface interactions might impact drivers' attention and efficiency in a specific driving situation when using ULEV. The findings are summarized as follows:

- Tab interface: Shows the highest ATR, which may indicate more cognitive load or less intuitive interaction, and results in the highest J/L, making it the least energy-efficient.
- TabAssist interface: Achieves the highest NGD and FR, indicating strong user engagement, and demonstrates the best energy efficiency with the lowest J/L, making it the most effective user interface in terms of both driver attention and energy efficiency.
- OledAssist interface: Shows a balanced performance with moderate NGD and FR, has the lowest ATR, suggesting a simpler or more intuitive interface, and provides better energy efficiency than the Tab interface but not as efficient as TabAssist.

The TabAssist interface is the most effective in terms of driver engagement and energy efficiency (Table 2).

Table 2: Energy efficiency results (less Joule/Laptime consumption is better)

	Tab	TabAssist	OledAssist
Average Joule/Laptime	123.12	104.47	110.15
Comparison (%)	100	85	89

Further investigation should involve recruiting more drivers to participate in the test, conducting the study under real race-like conditions, or utilizing a simulation environment to allow for more controlled data acquisition.

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