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Examining Factors Affecting Takeover Time in Automated Driving using Machine Learning Algorithms

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Abstract

This study, performed under the HADRIAN project, aims to investigate the factors affecting Takeover Time in Automated Driving, a critical safety Key Performance Indicator (KPI). The data were gathered through a driving simulator experiment as well as questionnaires which evaluated innovative HMI prototypes designed to enhance Automated Driving (AD) at SAE Levels 2 and 3. A safety and impact assessment methodology tailored to HADRIAN was developed, incorporating unique KPIs. Descriptive insights for these KPIs were formed to facilitate comparisons and substantiate the observed safety and impact advancements. Moreover, XGBoost feature analysis algorithms were deployed to obtain the most significant KPIs that affect Takeover Time from automated to manual driving. The key influential factors include the driver's trust in the HMI, followed by the frequency of takeover requests, the smoothness during takeover manoeuvres, and the specific HMI condition (baseline or HADRIAN HMI).

Keywords:

Autonomous Vehicles, and Human-Machine Interface (HMI)

1. Introduction

Road accidents present a significant public health concern, standing as the 8th leading cause of death globally, resulting in approximately 1.3 million fatalities yearly and a higher range of non-fatal injuries, estimated between 20 to 50 million [1]. The financial implications of these incidents are noteworthy; in 2005, the cost to prevent a single fatality in 31 European nations varied from 0.7 to 3.0 million Euros [2]. Further, European road accidents account for 0.4% to 4.1% of GDP, while the World Health Organization (WHO) approximates the global expense at roughly 3% of GDP. This highlights the profound influence of road accidents on health, societal, and economic sides [2–4]. Understanding the fundamental reasons behind these accidents is pivotal. Reports suggest that human errors contribute to as much as 94% of all road accidents [5]. Yet, advancements in automotive technologies, particularly the rise of Autonomous Vehicles (AVs), promise enhanced safety by minimizing human mistakes [6, 7]. As AVs evolve, there remains a need for Human-Machine Interfaces (HMIs) to facilitate effective communication between users and these Automated Driving (AD) vehicles. This objective was fundamental to the EU H2020 HADRIAN project, which focused on ensuring smooth interactions between drivers and automated systems. A critical aspect, to ensure smooth interactions between drivers and automated systems, that particular emphasis must be placed on is the understanding of factors affecting take-over requests during transitions from Automated Driving (AD) to manual control.

This research primarily aims to offer detailed insights into Key Performance Indicators (KPIs) related to new HMI designs for automated vehicles, conducted under the EU H2020 HADRIAN project. Then, the study focuses on understanding with Machine Learning algorithms the factors influencing Takeover Time in Automated Driving, a critical safety KPI for AD. More specifically, the study employs XGBoost feature analysis techniques to identify the most influential KPIs affecting the takeover time from automated to manual driving.

2. Methodology & Results

This study, performed under the HADRIAN project, focuses on evaluating the effects of innovative HMI systems on safety, driving performance, and driver perceptions, utilizing both driving simulation and survey responses. Within this framework, driving simulation experiments were carried out to determine if the HADRIAN HMI innovations offer enhanced safety and are more user-friendly, practical, and comfortable for drivers. More specifically, this study focuses on a driving simulator experiment that tested innovative prototypes that enhance AD predictability, availability, and continuity, and boost driver monitoring, HMI adaptiveness, and tutoring using Heads Up Display (HUD), LED strips, haptic cues on the steering wheel, and an interactive tablet. Simulated driving scenarios included driving sections with Automated Driving Levels 2 or 3 or manual and in parallel, drivers were instructed to perform a secondary task. Additionally, a specialized safety and impact assessment approach, tailored for HADRIAN, was formulated utilizing distinct KPIs. These KPIs were measured through driving performance metrics captured by the simulator, eye-tracking, and subjective feedback gathered from surveys. The KPI-centric assessment involves nine KPIs focused on safety and driving performance, alongside another nine assessing the system impact on driver perceptions (refer to Table 1). Descriptive analyses were employed to compare and validate the safety and impact enhancements introduced by the HADRIAN system, and simultaneously leveraging machine learning algorithms to explore the factors/KPIs influencing Takeover Time in Automated Driving.

Table 1 – List of KPIs for safety & impact assessment of HADRIAN innovations

KPI ID	*KPI*
KPI 1.1	Take Over Maneuver Safety Evaluation
KPI 1.2	Take Over Request Awareness Time
KPI 1.3	Take Over Time
KPI 1.4	Distraction
KPI 1.5	Conflicts

KPI 1.6	Automation Engagement	• Level 2 • Level 3
KPI 1.7	Close Interactions	
KPI 1.8	Number of Transitions	• AD → Manual • Manual → AD
KPI 1.9	Driving Measurements	• Speeding Duration • Speed Over the Limit • Harsh Cornerings • Harsh Brakings • Harsh Accelerations
KPI 2.1	Acceptability Ratings	
KPI 2.2	Subjective Workload	
KPI 2.3	Comfort	
KPI 2.4	Usability	
KPI 2.5	Comprehensibility	
KPI 2.6	Intend to Use	
KPI 2.7	Trust	
KPI 2.8	Control Feeling	
KPI 2.9	Safety Feeling	

The background as well as the development of this assessment methodology was given to past deliverables of the project (https://hadrianproject.eu/results/) and previous and oncoming publications that can be found online.

2.1 Integrated fluid HMI

In the driving simulation study, 20 participants drove a standard “baseline” HMI, while 19 used a HADRIAN HMI referred to as the “Integrated Fluid HMI.” To capture fully the results below, it is essential to outline the study specifics. The HMIs underwent testing in the “Virtual Vehicle” driving simulator. The HADRIAN HMI aimed to enhance automated driving predictability, availability, and continuity. A pivotal aspect was the provision of a 5-second takeover window for Automated Driving Level (ADL) 2 and a 15-second window for ADL3, with ADL3 duration being predictable by road infrastructure integration. Through driver monitoring, such as tracking eye movements to identify visual distractions and using a camera to monitor hands-off-wheel instances, unsafe driving conditions were intended to be detected. Additionally, pre-drive tutoring via instructional videos and in-drive guidance, including verbal cues and the option to revisit specific tutorial segments during AD, aimed to educate drivers on optimizing automated driving features and understanding their roles across varied driving scenarios. Collectively, these components contribute to a fluid HMI, customizing information, feedback, and alerts based on the driver's state and requirements.

Therefore, the integrated fluid HMI offers the following primary functionalities:

- 5-second takeover intervals for ADL2 and 15-second intervals for ADL3, with countdown notifications presented to the driver.
- Pre-determined time frames for ADL3 driving, with the duration displayed for the driver.
- Pre-drive instructional videos detailing driving functionalities, proper system utilization, and driver obligations.

- Audible instructions and feedback regarding system operation, along with adaptive tutoring during the drive based on eye movement and takeover duration during transitions.
- Alerts triggered by identified visual distractions or hands-off-wheel scenarios during either manual or ADL2 driving, with timing adjusted according to the driving mode.
- Take-over assistance by providing countdown information, current speed limit, and information about upcoming obstacles, as well as haptic cues at the steering wheel.
- Insights into vehicle behaviour in ADL3 (current speed, detected speed limit, upcoming manoeuvres)
- Support of mode awareness, mode changes, and alerts via ambient lighting.

In developing the integrated fluid HMI, various interfaces were incorporated and integrated to fulfill specific roles within the HMI framework. Figure 1 offers a summary of the components and the configuration within the driving simulator utilized for the experimental study.

Figure 1 - Integrated fluid HMI components of the Virtual Vehicle holistic simulator study

In addition to the HADRIAN HMI, the baseline HMI plays a pivotal role in the assessment methodology, serving as a "baseline" to compare the HADRIAN HMI against other prevailing or "state-of-the-art" advancements. To define this baseline HMI, the setup underwent particular consideration and rigorous evaluation using the Virtual Vehicle driving simulator. For an equal comparison, identical takeover durations were assumed for both HADRIAN and baseline conditions in ADL2 and ADL3, specifically 5 seconds for ADL2 and 15 seconds for ADL3. However, unlike the HADRIAN setup, these durations were not displayed by the HMI in the baseline condition. Additionally, consistent with contemporary vehicles equipped with driving aids, a hands-off-wheel alert would be activated during ADL2 in the baseline setup. Analogous to the fluid HMI, a warning would trigger if the driver removed hands from the wheel for over three seconds. Beyond these aspects, the baseline HMI did not adjust based on the driver's condition nor offer instructional guidance. Figure 2 highlights the principal features of the baseline HMI.

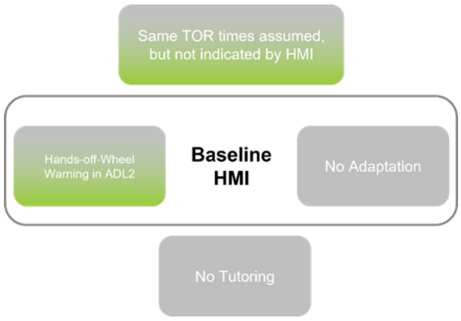


Figure 2 - Key features of the baseline HMI

The descriptive findings and the deployment of machine learning algorithms, based on the HADRIAN-tailored safety and impact assessment, on data from this simulator study are fully reported in the subsequent subsections.

2.2 Safety KPIs

In Figure 3, it is illustrated the driving objective safety KPIs (KPI 1.1 - 1.9) for Baseline HMI (gray) and HADRIAN HMI (green) conditions. Each graph displays participants' KPI performance, using axes to denote participant IDs and corresponding KPI values. These graphs highlight variations attributable to HADRIAN innovations, with pie charts further categorizing harsh driving events by condition.

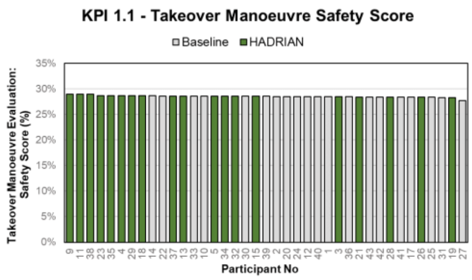
For KPI 1.1 "Takeover Manoeuvre Safety Score" participants generally display consistent scores, with a noticeable positive trend under HADRIAN conditions. This improvement is attributed to enhanced driver awareness and support during takeover maneuvers, facilitated by informational videos and system cues within the HADRIAN settings. Similarly, in KPI 1.2 "Take Over Request Awareness Time", HADRIAN participants record shorter awareness times, benefiting from enhanced informational cues such as countdowns and video guidance. As a result, in KPI 1.3 "Take Over Time" participants under HADRIAN conditions exhibit extended takeover times, allowing drivers for more comprehensive environmental assessments before transitions.

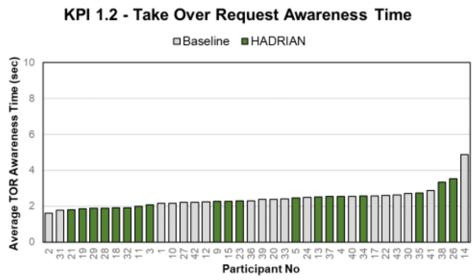
The combined analysis of KPIs 1.1, 1.2, and 1.3 underscores HADRIAN positive impact on takeover performance, enhancing driver preparedness and efficiency. Moreover, HADRIAN contributes to smoother takeover maneuvers, as evidenced by improved driver responses.

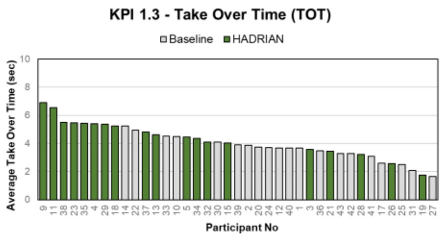
Regarding KPI 1.4 "Distraction Percentage" Baseline participants measured elevated distraction levels, highlighting HADRIAN effectiveness in mitigating distractions. Conversely, KPI 1.5 "Number of Conflicts" reveals comparable conflict frequencies across conditions, suggesting potential areas for system refinement. Similarly, KPIs 1.6 "Automation Engagement ADL2 & 3" reflect consistent durations across both conditions, with slight variations attributed to study design and system constraints. KPI 1.7 "Conflicts (Frequency of TTC <3s)" demonstrates similar frequencies in both conditions, likewise the KPI 1.5, the absence of a specific system for reducing headways could produce this result.

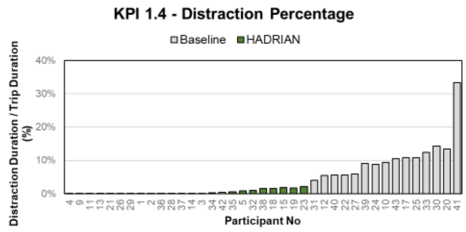
For KPIs 1.8 “Number of Total Transitions” and 1.9 “Driving Measurements”, minimal differences are observed in transition frequencies and speed-related metrics, with HADRIAN participants occasionally displaying higher values. Specifically, HADRIAN participants exhibit more aggressive braking behaviours, potentially influenced by speed indications within the HADRIAN HUD. Overall, these findings emphasize HADRIAN significant contributions to enhancing safety and efficiency in automated driving scenarios.

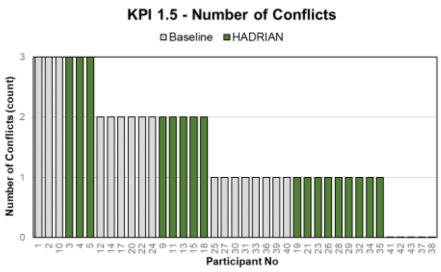
In summary, while certain KPIs indicate comparable results across conditions, HADRIAN contributions notably optimize takeover processes. Further insights into takeover time and associated KPIs will be explored through XGBoost analysis, enhancing our comprehension and potential advancements in automated driving scenarios.

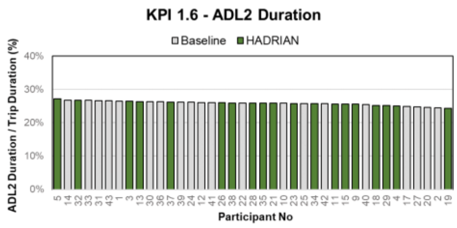


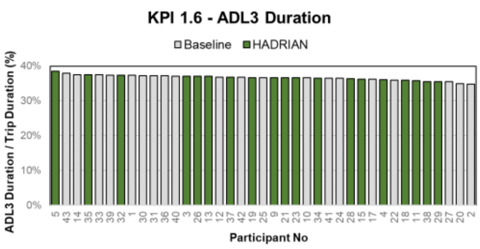


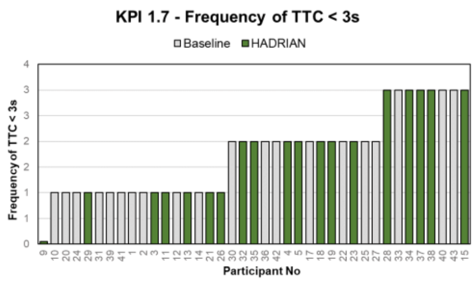












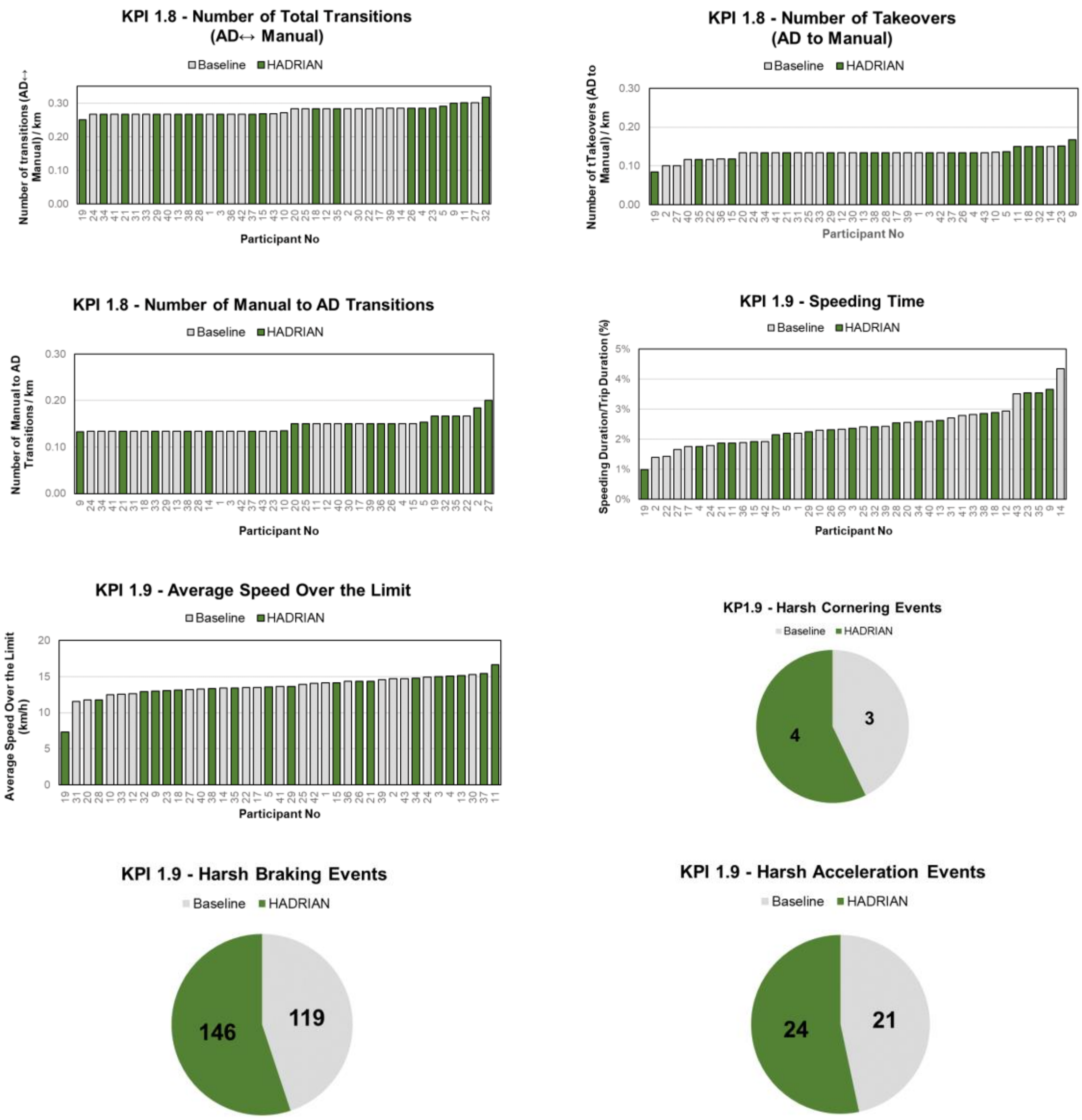


Figure 3 - KPI values of driving objective safety for each participant per condition

2.3 Perceived impact KPIs

In a manner consistent with the previous subsection, the driver perceived impact KPIs, specifically KPIs 2.1 - 2.9, are illustrated in the provided graphs (Figure 4). These graphs present participants' ratings from completed questionnaires, distinguished by different colors representing the Baseline and HADRIAN driving conditions. Concerning KPI 2.1 “Acceptability Ratings” a preference and inclination towards the baseline conditions appear evident. This suggests that participants may favor the simplicity and non-interventional nature of the baseline conditions over the HADRIAN innovations. Regarding KPI 2.2 “Subjective Workload” HADRIAN participants generally perceive less effort in managing driving tasks compared to their baseline counterparts, although a minority found the HADRIAN simulations more demanding. This outcome aligns with the conclusion that HADRIAN innovations enhance situational awareness, thus minimizing cognitive load.

For KPIs 2.3 “Comfort” and 2.4 “Usability” HADRIAN participants tend to rate their driving experience slightly higher, suggesting that HADRIAN conditions offer a more comfortable and user-friendly driving environment.

In contrast, KPIs 2.5 “Comprehensibility” and 2.6 “Intend to Use” reveal lower rankings for HADRIAN conditions relative to baseline. This may be attributed to the increased complexity associated with HADRIAN innovations, potentially deterring future utilization. On the contrary, for KPIs 2.7 “Trust” and 2.8 “Control Feeling” HADRIAN participants assign moderately higher ratings to automated systems, underscoring the efficacy of HADRIAN innovations in introducing confidence and perceived reliability. Interestingly, KPI 2.9 “Safety Feeling” indicates minimal differences between conditions, with the highest safety perceptions reported during HADRIAN HMI scenarios.

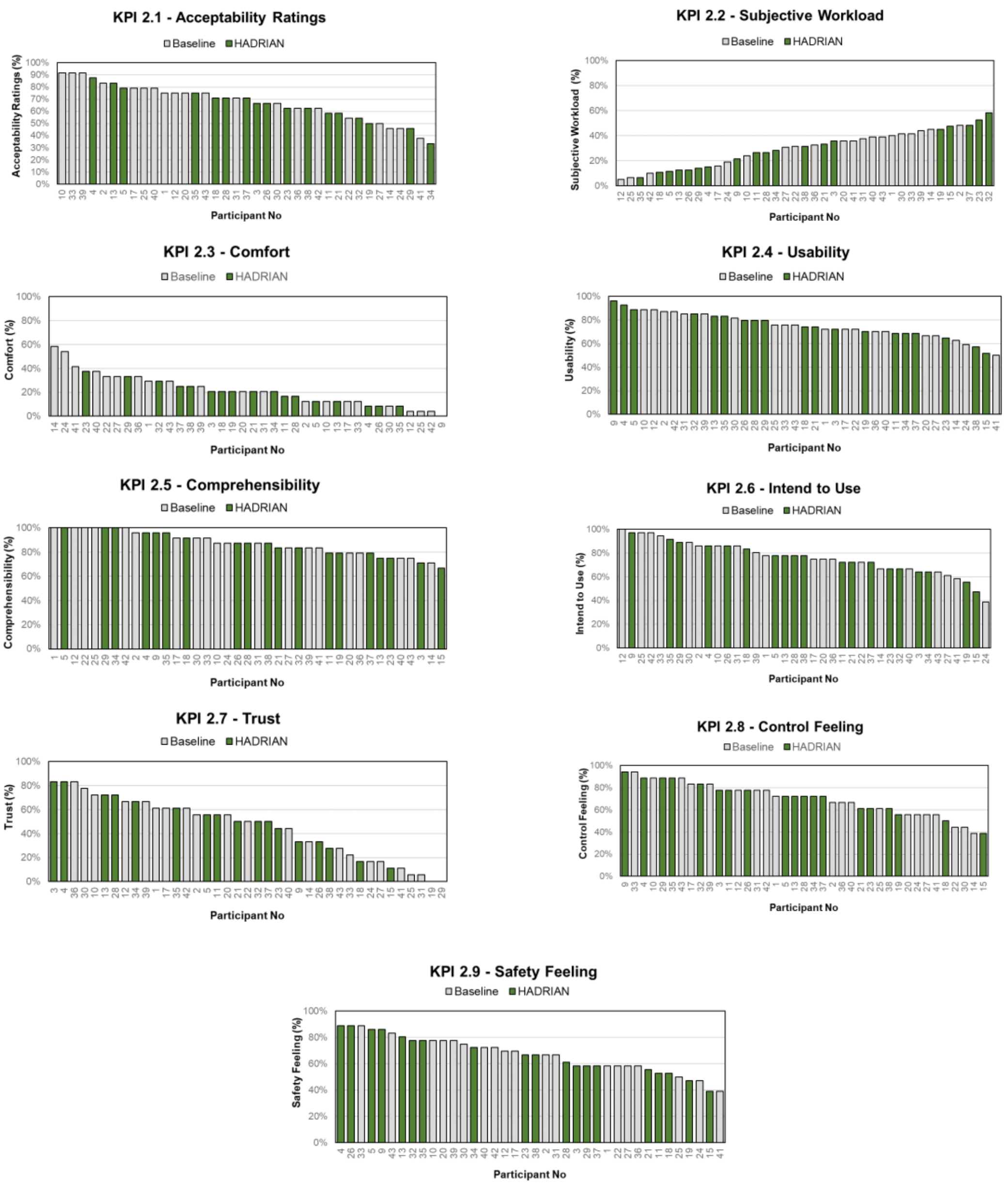


Figure 4 - KPI values for driver perceived impact for each participant per condition

2.4 Feature Importance of Takeover Time

The XGBoost algorithm was run within R-Studio environment using the xgboost package. Initially, the data underwent a random split: 75% served as the training set, and the remaining 25% as the test set. Subsequently, various learning rates (eta) ranging from 0.01 to 0.3 were evaluated for each XGBoost ensemble to determine the optimal model for takeover time (KPI 1.3). The learning rate, as described by Murphy (2012) [8], is a crucial parameter that influences the step size during each iteration towards minimizing the loss function. To prevent overfitting, K-fold cross-validation was implemented to identify the optimal iteration number within the XGBoost algorithm. Each model underwent K-fold cross-validation across approximately 200 iterations to ensure the most suitable iteration.

The defined parameters for the XGBoost model for takeover time were provided as follows:

- Learning rate (eta): 0.01–0.3
- Gamma: 1
- Maximum tree depth: 6
- Subsample ratio of the training instances: 0.8
- Subsample ratio of columns when constructing each tree: 0.5

The extracted errors from the XGBoost model provide valuable insights into its predictive performance (Table 2). A Mean Squared Error (MSE) of 1.377, Mean Absolute Error (MAE) of 0.979, and Root Mean Squared Error (RMSE) of 1.174 indicate the average magnitude of errors between predicted and actual values, with lower values suggesting better accuracy. Additionally, an accuracy rate of 0.749 further emphasizes the model capability to correctly predict outcomes.

Table 2 – Error values on test set predictions

Error Metrics	***Values***
Mean Squared Error (MSE)	1.377
Mean Absolute Error (MAE)	0.979
Root Mean Squared Error (RMSE)	1.174
Accuracy	0.749

Utilizing the implemented XGBoost model, Figure 5 and Table A.1 (in the Appendix) present the extracted feature importance of takeover time. The model was fed based on the aforementioned KPIs, along with additional factors such as simulator route distance, duration, participant number, and the HMI condition (HADRIAN or baseline HMI). Table A.1 in the Appendix specifically details the gain, cover, and frequency associated with the provided features. Figure 5 illustrates the impact of takeover time, outlined by the gain scores derived from the XGBoost model.

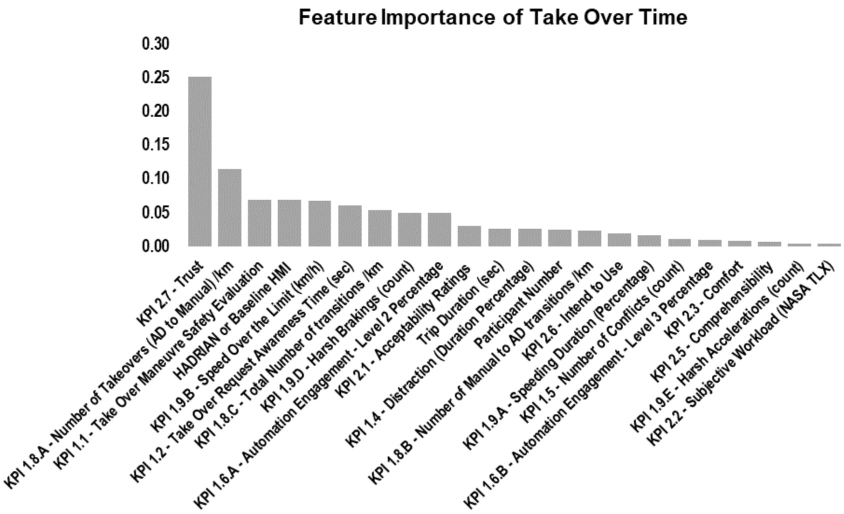


Figure 5 – Feature Importance using XGBoost on Takeover Time

Analyzing the gain scores from feature importance reveals several key insights regarding takeover time:
The foremost influential factors include the driver's trust in the HMI, as gathered from survey responses during the experiment, followed by the frequency of takeover requests, the safety score during takeover maneuvers, the specific HMI condition (baseline or HADRIAN), and the driver's speeding behavior during manual driving segments.

Notably, the driver's trust in the HMI appeared as the dominant factor affecting takeover time, suggesting that perceptions regarding HMI trust significantly influence the driver's responsiveness during automated driving. Additionally, the frequency of takeover requests serves as a pivotal alert mechanism, preparing the driver for imminent takeover requests. The safety score during takeover maneuvers plays a crucial role, utilizing metrics like speed, longitudinal acceleration, and deceleration to gauge safety [9]. This underscores an interdependent relationship between the smoothness of takeover maneuvers and takeover time. Moreover, the HMI condition, whether baseline or HADRIAN, proves significant, proving the tangible impact of HADRIAN HMI advancements on takeover time. Concurrently, aggressive speeding behaviors during manual driving phases correlate with variations in takeover time.

Further important KPIs include takeover request awareness time, emphasizing drivers' adeptness at scanning critical driving environment information, transitions between AD levels per kilometer, both from and to manual and AD modes, instances of harsh braking indicative of manual driving aggressiveness, and the duration of AD level 2 engagement relative to the entire route.

3. Conclusions

In summary, the comprehensive analysis of various KPIs underscores significant advancements in the performance and user experience metrics when employing the HADRIAN HMI prototypes compared to baseline configurations. Specifically, notable enhancements are observed in KPIs such as “Takeover Manoeuvre

Safety Score", "Take Over Request Awareness Time", "Take Over Time", "Distraction Percentage", "Subjective Workload", and "Control Feeling". These improvements collectively signify a more smooth takeover process, reduced driver distraction, moderated perceived mental workload, and enhanced control perception with the HADRIAN HMI.

Moreover, integrating the XGBoost results further validates these findings, emphasizing the essential role of driver trust in the HMI, frequency of takeover requests, maneuver smoothness after takeover requests, and specific HMI conditions (baseline or HADRIAN) as critical determinants influencing takeover time. Such insights align with the broader objectives of the HADRIAN project, fostering human-centered assessment methodologies. Understanding takeover mechanisms and safety metrics seems essential to optimize human-machine interactions within autonomous vehicles, as exploited by HADRIAN and any other HMI-related stakeholders in order to improve AD safety in the automotive landscape.

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Appendix

Table A.1 – Feature importance of Takeover Time - XGBoost algorithms

Feature	***Gain***	***Cover***	***Frequency***
KPI 2.7 - Trust	0.253	0.119	0.109
KPI 1.8.A - Number of Takeovers (AD to Manual) /km	0.115	0.132	0.116
KPI 1.1 - Take Over Maneuvre Safety Evaluation	0.070	0.056	0.054
HADRIAN or Baseline HMI	0.070	0.072	0.070
KPI 1.9.B - Speed Over the Limit (km/h)	0.068	0.064	0.078
KPI 1.2 - Take Over Request Awareness Time (sec)	0.061	0.077	0.078
KPI 1.8.C - Total Number of transitions /km	0.054	0.071	0.070
KPI 1.9.D - Harsh Brakings (count)	0.050	0.086	0.078
KPI 1.6.A - Automation Engagement - Level 2 Percentage	0.049	0.062	0.062
KPI 2.1 - Acceptability Ratings	0.031	0.027	0.039
Trip Duration (sec)	0.026	0.022	0.039
KPI 1.4 - Distraction (Duration Percentage)	0.026	0.026	0.031
Participant Number	0.024	0.029	0.031
KPI 1.8.B - Number of Manual to AD transitions /km	0.024	0.025	0.023
KPI 2.6 - Intend to Use	0.019	0.026	0.023
KPI 1.9.A - Speeding Duration (Percentage)	0.016	0.038	0.031
KPI 1.5 - Number of Conflicts (count)	0.011	0.020	0.016
KPI 1.6.B - Automation Engagement - Level 3 Percentage	0.010	0.018	0.016
KPI 2.3 - Comfort	0.009	0.005	0.008
KPI 2.5 - Comprehensibility	0.007	0.009	0.016
KPI 1.9.E - Harsh Accelerations (count)	0.004	0.007	0.008
KPI 2.2 - Subjective Workload (NASA TLX)	0.004	0.007	0.008

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