Promoting Level-Compliant Behavior in Automated Vehicles: Evaluation of an AI-based Solution

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Abstract: This paper presents an AI-based solution to promote level-compliant behavior in automated vehicles. By integrating driver monitoring and human machine interaction, the system detects and addresses non-compliant behavior through multimodal interactions. A user study with 61 participants evaluated the system's usability and effectiveness, revealing high comprehensibility and usability scores. The AI agent, trained using reinforcement learning, adapts to various driving contexts and user states, ensuring safe and comfortable interactions. The findings highlight the importance of adaptive, multimodal approaches in enhancing driver compliance and safety in partially automated driving.

Keywords: Automated Driving, Human Machine Interaction, Level-compliant Behavior, Reinforcement Learning.

1 Introduction

The automotive industry is constantly working towards fully automated vehicles in all conditions, but still there is a long way to go. And even when fully automated driving is possible (SAE level 4 and 5 [1]), in parallel there will be still partly automated vehicles in operation. Partly automated vehicles can control lateral and longitudinal direction under specific conditions and thus, it is a gain in comfort for a driver. However, it also introduces challenges, like ensuring driver's mode awareness [2], take-over readiness [3] or avoiding drowsiness [4] during monitoring the automation. To improve comfort and safety as well as mitigate the named challenges of partly automated driving, the approach of level-compliant behavior was introduced in [5]. This approach foresees vehicles with varying automation levels while the driver needs to comply with a certain user role, e.g. monitoring the vehicle or being ready for take over requests. Each user role allows a certain behavior (e.g. using smartphone as standby driver on SAE Level 3). Once the driver's behavior is not compliant with the current role, an interaction is initiated to ensure that the driver operates the vehicle safely. To ensure level-compliant behavior, current production systems of partly automated driving often apply a so-called dead man's switch. Most common for this approach, level-compliant behavior is proven by touching the steering wheel or slight steering [5]. However, especially if the user over trusts automation, such a one-sided approach for driver

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monitoring is not prone to misuse [6]. In this paper[2], we propose an Artificial Intelligence (AI)-based solution to detect and select an interaction to avoid driver's non level-compliant behavior. By that, promoting driver's level-compliant behavior was approached holistically from driver monitoring as well as from Human Machine Interaction (HMI) perspective [5]. This solution was evaluated in a user study with 61 participants considering usability as well as performance measures of the system. Results of this evaluation are highlighted and recommendations for supporting level-compliant behavior are postulated.

2 Approach

To follow this holistic approach, a test vehicle was built up which comprises visual, auditory, and tactile channels (e.g. displays, speakers, vibrotactile seat) for HMI as well as sensors (e.g. near-infrared cameras) to monitor the driver's state. To evaluate the usability of the interaction chosen by the AI-based level-compliant agent introduced in Section 2.2, a study (Section 2.1) on public roads was conducted. Different levels of automation were simulated in this so-called Wizard of Oz-vehicle [7]. It was aimed to evaluate the usability of the system and the performance of the implemented AI-based solution with high external validity, so under conditions that are closest to reality as possible.

2.1 User study

Participants: Participants were recruited by an agency to ensure a uniform distribution of age and gender. In total, 61 participants completed the study. 30 participants were females and 31 males. Their age ranged from 18 to 65 years (*M* = 39.4). Knowledge of German language was required to understand the instructions and a valid driving license was prerequisite of participation.

Procedure: First, after a short welcoming, participants gave their informed consent and were informed about the procedure and possible risks of taking part in the study. Following, participants answered questions describing their demographic data and current state. Then, the different user roles "monitoring driver" (SAE L2+) and "standby driver" (SAE L3) were introduced. Participants were instructed that non level-compliant behavior leads to an interaction by the system via the level-compliant agent. Lastly, they were informed that a person sitting next to them on the right front seat and separated by a curtain, is a safety driver who monitors the automation and takes over steering, accelerating, or braking only if needed (in fact this person was the active driving wizard during the whole drive [7]).

Second, participants completed a 30-minute-long drive on public roads. During the drive, they experienced different user roles depending on different sections of the route. The sections were defined according to relevant changes in infrastructure. Overall, they took on the roles of "monitoring driver" (SAE Level 2+) and "standby driver" (SAE Level 3). Throughout the entire drive, the AI-based solution for detecting and preventing non level-compliant behavior was active. The participants could perform non-driving related activities the whole time (e.g., reading, watching videos, engaging with a tablet or smartphone, drinking). If the respective non-driving related activity did not correspond to the current

[2] Paper was supported by funding from the Federal Ministry of Economic Affairs and Climate Action as study was conducted in the project KARLI.

user role, meaning the person was non level-compliant, the level-compliant agent would interact with the most suitable modality. While being standby driver, participants rated the understandability of these selected modalities on a single item scale from 1 = '*not understandable at all*' to 7 = '*completely understandable*' on a tablet located at the center stack of the vehicle two times.

Third, after the drive, participants received a questionnaire with different components: Most importantly, they evaluated the usability of the overall system via the System Usability Scale (SUS) [8]. The described variables were used to assess the understandability and usability of the modalities that the level-compliant agent selected for interaction. Furthermore, participants had the chance to give qualitative feedback in an interview after the drive. Finally, participants were informed about the use of the so-called Wizard-of-Oz approach and were asked to excuse the deception.

2.2 AI-based level-compliant agent

We have devised an AI-based agent that regulates user engagement in a fashion that correlates with established levels of compliance. This component is referred to as the level-compliant agent and has been trained within a simulated environment as presented in Figure 1. Through reinforcement learning technique, the agent receives a reward signal that informs its compliance with established objectives in user interactions. These interactions' states comprise a combination of user and environmental data. Once the agent undergoes training within the simulation, it can then be incorporated into the vehicle, serving to garner valid data during real test drives. Based on this data pool, the simulation parameters are then updated, prioritizing measured distributions, ensuring optimal agent conduct within real conditions by retraining and optimization.

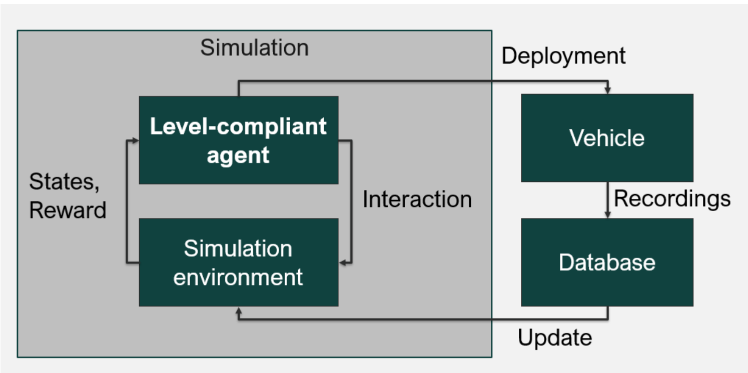

Figure 1: Overview of the level-compliant agent.

The developed level-compliant agent can process a diverse range of inputs, including the user's gaze direction, head orientation, and current activity, along with the prevailing vehicle volume and traffic complexity. On this basis, the agent seeks to determine whether the user is acting in a level-compliant manner while additionally assessing the most appropriate modality through which interactions should occur. Timing requirements, such as interactions following a threshold of non level-compliant behaviors, are also efficiently managed by the level-compliant agent.

For the level-compliant agent we used reinforcement learning (RL) for the modelling. The following reasons support the use of an AI-based solution, particularly the use of RL:

- Sensor data is subject to noise and uncertainties, making a purely algorithmic solution difficult to handle in combinatorics.
- The behavior of the test subjects showed that while there is a main distribution in behavior, there are also subjects whose behavior deviates significantly from the "standard". Therefore, an algorithmic solution is difficult to implement.
- Furthermore, the model must be able to adapt to specific users over time to achieve a personalized solution. RL methods have proven particularly effective in this regard.

The model of the level-compliant agent uses continuous inputs and outputs. In our experiments, we achieved better results with this approach than with categorical variables. Table 1 shows the input and output variables, including the value range. The output values are normalized between -1 and 1, where a level-compliant value of -1 corresponds to a non-level-compliant state. The modality values should be interpreted such that the modality with the highest value is the currently preferred interaction modality.

Table 1: Input and output variables of the level-compliant agent.

Type	Name	Value range
Input	Head orientation (yaw axis)	[-180; 180]
Input	Head orientation (pitch axis)	[-90; 90]
Input	Gaze direction x axis	[-1; 1]
Input	Gaze direction y axis	[-1; 1]
Input	Eye opening state	[0; 1]
Input	Activity calling	[0; 1]
Input	Activity reading	[0; 1]
Input	Activity drinking	[0; 1]
Output	Level-compliant value	[-1; 1]
Output	Visual modality	[-1; 1]
Output	Auditive modality	[-1; 1]
Output	Tactile modality	[-1; 1]

The application also includes temporal conditions for levels 2 and 3, meaning the time after which an interaction with the user is initiated, which is realized through frame stacking. In this process, the last N input signals are combined into a matrix and then presented to the model as input data, enabling it to learn temporal relationships. For SAE L2+ (monitoring driver), a history of N = 20 was chosen, and for SAE L3 (standby driver), N = 50 was chosen.

The training process of the level-compliant agent model consists of four steps. In step one, new sensor states, i.e., the input data for the model, are generated using a simulation. This simulation generates the sensor states based on distributions determined from real data. In step 2, the model is executed, determining the recommended modalities and the level-compliant value. In step 3, the reward for the model is calculated, which is used in the final

step to adjust the model parameters of the level-compliant agent. All steps are repeated until a defined number of iterations (episode length) are completed.
For the training of the level-compliant agent we designed a reward function consisting of two components. The first component evaluates the level-compliant value, while the second takes the modalities into consideration. The first reward component is defined as follows:

$$r_{LKV} = 1 - \left| \frac{y_{LKV} + 1}{2} - \frac{K}{N} \right|$$

Thereby, K is the number of level-compliant states in the input history and y_{LKV} is the prediction of the level-compliant value. This ensures, that the level-compliant value decreases when the number non level-compliant states decreases and thus models the temporal behavior. The second component r_M computes the reward for the modalities. Thereby, the predicted values y_k are compared with values from a database v_k, which were selected based upon the activities of the users. The second reward component is defined as:

$$r_M = \sum_{k=v,a,t} \frac{1}{2}(2 - |y_k - v_k|)$$

The indices v, a, t correspond to the visual, auditive and tactile modality. Both reward components can then be combined to the final reward function:

$$r = \begin{cases} \frac{1}{2}(r_{LKV} + r_M), & K = 0 \\ r_{LKV}, & K \neq 0 \end{cases}$$

Note, that only when all states in the history are non level-compliant both components are used for calculating the reward, since only then an interaction with the user is required.

3 Results & Discussion

3.1 Usability Study

During the drive, participants rated the comprehensibility of the overall system on a single-item scale at two points in time. This variable was analyzed descriptively. After the drive, participants rated the usability of the overall system with the SUS. For analyzing the SUS, the SUS-Score was deducted, and the overall rating was classified accordingly [8].
Comprehensibility rating: During the drive, participants perceived the interactions via the selected modalities as 'highly understandable' (*M* = 6.4, *SD* = 0.7; 1 = '*not understandable at all*' to 7 = '*completely understandable*').
SUS-Score: After the drive, participants rated the usability according to the SUS. This resulted in a SUS-Score that can be categorized according to [8] as "very high" (*M* = 80.1, *SD* = 13.0). Figure 2 shows the distribution of the SUS-Score.

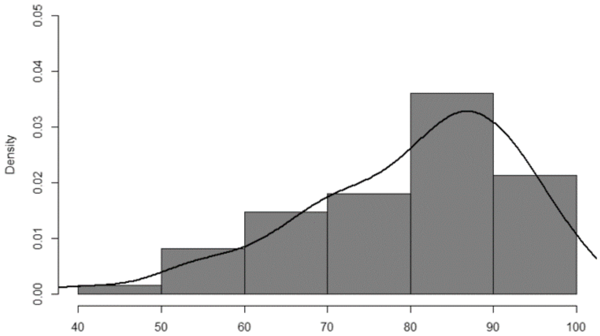

Figure 2: Density of SUS-Scores. The axis of abscissas denotes the SUS-Score.

Summary: Overall, the multimodal and adaptive approach of the AI-based level-compliant agent to promote level-compliant and avoid non level-compliant behavior was experienced as highly understandable and its usability was rated as high. Similarly, additional qualitative feedback by the participants given in interviews after the drive highlighted the importance of multimodality (visual, auditory, and tactile interaction) for an HMI to promote level-compliant behavior. In conclusion, the adaptivity of the AI-based solution does not hinder, but rather supports the usability and understandability of the interaction.

3.2 Training and performance evaluation of the level-compliant agent

3.2.1 Training evaluation

For the training of the level-compliant agent we used the Proximal Policy Optimization (PPO) algorithm [9]. During training we utilized multiple criteria to select a stable model e.g., early convergence, steady and monotonic increase of reward and maximum cumulative reward. By hyperparameter tuning we show which settings yields a stable training and a high reward, while minimizing the model capacity.

In this section, we discuss the results obtained during the training of the level-compliant agent. Various models with different hyperparameters were trained for this purpose. First, we analyzed the reward curves, i.e., the cumulative reward over the training iterations, as shown in Figure 3. We evaluated how consistently (in terms of stability and speed) a maximum reward is achieved. The diagram shows six trained models, which exhibit a steeper reward curve in the first 200.000 iterations, indicating that the models are learning the task. In the second phase, the maximum rewards converge without significant fluctuations in the reward curve.

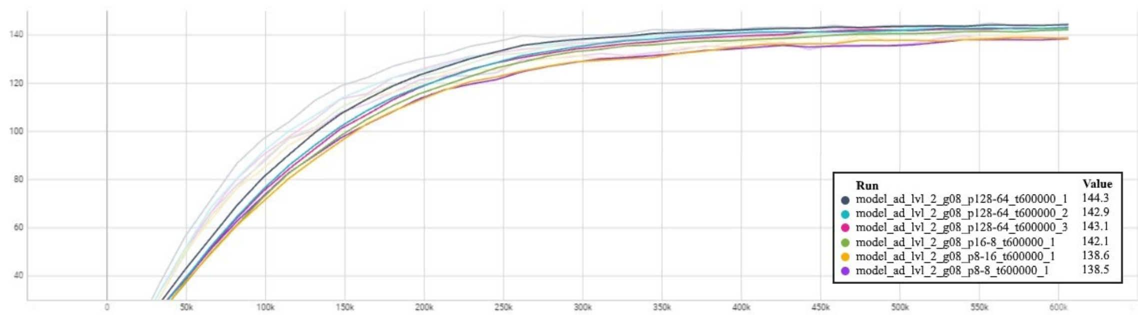

Figure 3: Example of reward curves of the trained level-compliant agents. The x-axis denotes the episodes and the y-axis shows the cumulative reward.

To finally select the best model for the level-compliant agent, a hyperparameter search was conducted regarding the episode (iterations), step size (number of samples for averaging the reward), gamma (agent's horizon), and architecture (number of neurons per layer). Table 2 shows an excerpt from the results of the hyperparameter search with the corresponding reward and loss for both level 2 and level 3 models. The models with the highest cumulative reward were then selected for further evaluation.

Table 2: Excerpt of the hyperparameter experiments to train the RL model.

ID	Level	Episode	Step	Gamma	Architecture	Reward	Loss
1	3	350000	8192	0,2	[128, 64, 64]	232	0,050
2	3	350000	512	0,2	[128, 64, 64]	230,4	0,004
3	3	600000	16384	0,2	[128, 64, 64]	230,3	0,054
4	3	350000	2048	0,2	[128, 64, 64]	230,1	0,039
5	3	1000000	8192	0,8	[128, 64, 64]	227,4	0,035
6	2	600000	16384	0,2	[10, 128, 64, 64]	150,7	0,029
7	2	1000000	8192	0,8	[10, 128, 64, 64]	149,8	0,081
8	2	1000000	16384	0,8	[10, 128, 64, 64]	149,1	0,044
9	2	600000	16384	0,8	[128, 64, 64]	148,6	0,014
10	2	600000	16384	0,8	[10, 128, 64, 64]	148,5	0,166

3.2.2 Test case evaluation

Figure 4: Measurements of an example test case. The x-axes are described in Table 1.

For the verification of the level-compliant agent, 110 test cases were recorded, where each test cases consists of two activities lasting for 30 seconds each. Thereby, 98 test cases are passing while 12 cannot be handled by the current setup, which is due to limitations of the upstream perception algorithm (e.g., detecting the eye gaze direction) and uncommon driver behavior. Figure 4 shows one example test case, where a person is transition from the task of looking through the windshield (level-compliant) to looking at a storage compartment (non level-compliant) to search for an object. In this example, it is assumed that the driver is in the role of the monitoring driver. The upper diagram shows the level compliance value and the modality probabilities. Here we can see that in the first half, the user is predicted to be level-compliant, and in the second half, the user is not level-compliant, as expected. For each application case, we calculate a test case score that sums the difference between the expected and predicted value for level compliance. The smaller the value, the better the level-compliant agent handled the test case. All values are then averaged to obtain a final test case value, which is used to evaluate the performance of the trained agents. In this way, we found that the model with the highest reward value does not necessarily have the lowest test case value. Therefore, to find the best agent, we made a compromise between reward and test case value.

Table 3 shows all test cases and their test case values for each test user as well as for levels 2 and 3. On average, a test case value of 0.29 was obtained. We marked the test case as failed if the value was 0.7 (heuristically determined) or higher, which is highlighted in the table. Furthermore, the test cases helped us optimize the system regarding the application case and specifically track where further optimizations were needed.

3.2.3 Study data evaluation

Apart from the test case verification, we evaluated the trained level-compliant agent on the data obtained from the user study. As a core metric, we used the *effectiveness* score, which considers the total number of non level-compliance phases, the time of the complete drive and the time of the phases. It is defined as follows:

$$e = 1 - \frac{1}{2}\left(\frac{\sum_i^N t_i^s}{T} + \tanh\left(\frac{N}{2T_{min}}\right)\right)$$

Here, N is the total number of sequences (phases of non level-compliance), T defines the total driving time, and t_s is the respective time of a sequence. The effectiveness value can ideally take the value of 1 if there are no non level-compliant phases. The first term ensures that the duration of the sequences should be as minimal as possible relative to the total driving time. The second term regulates the number of sequences, as multiple very short sequences during a long drive would lead to a high value.

The final evaluation study consisted of 61 test drives, each lasting approximately 30 minutes. Each drive was conducted by a different user to achieve maximum variation. Figure 5 shows the effectiveness value for all test drives. On average, we achieved a value of 0.8 with a mean number of sequences of 24.36. This emphasizes that the developed model is robust for a large user group, which aligns with the achieved SUS. However, there are some cases where our system does not work, mostly due to uncertainties or errors in the sensor signals.

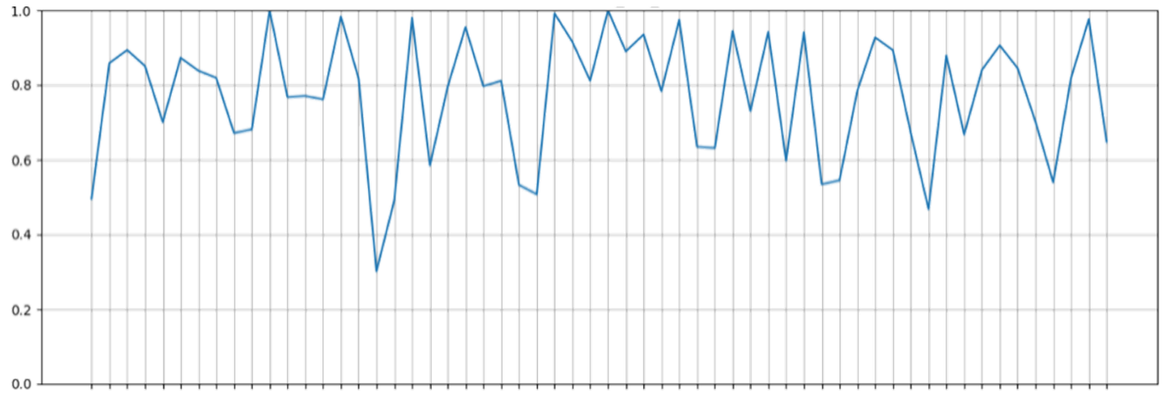

Figure 5: Effectiveness score of all test drives in the study. Each data point on the x-axis represents a participant in the study, while the y-axis depicts the effectiveness score.

4 Conclusion

In conclusion, the approach of the AI-driven agent to select the most suitable modality to promote level-compliant behavior was highly understandable and leading to a very high usability of the system. Hence, integrating driving context, user state, and activity to select a modality is crucial for a successful interaction to promote level-compliant behavior. For a safe and comfortable user behavior in the context of automated driving, a multimodal HMI is essential. The adaptive selection of different modalities according to human behavior to promote level-compliancy supports usability and understandability. To even further improve safety and comfort as well as overall user experience research is also required for agent development with long term personalization along with emphasis on more comprehensive and realistic simulation on behavioral and physiological data.

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Appendix

Table 3: Test cases values for each test case and test user.

ID	Test case	User 1		User 2		User 3		User 4	
		L2	L3	L2	L3	L2	L3	L2	L3
1	Looking through windshield → use smartphone	0.22	0.27	0.06	0.02	0.08	0.57	0.13	0.07
2	Looking through windshield → look into left storage compartment	0.06	0.66	0.08	0.02	0.18	0.45	0.12	0.02
3	Looking through windshield → close eyes (sleeping)	0.07	0.1	0.07	0.06	0.07	0.09	0.08	0.12
4	Look at left mirror → look at instrument cluster	**0.82**	**1.26**	0.46	0.35	0.45	0.08	0.52	0.0
5	Look at center stack display → looking through windshield	0.2	0.05	0.07	**0.74**	0.2	0.03	0.3	0.56
6	Look at instrument cluster → looking through windshield	0.01	**0.99**	0.61	0.57	0.04	0.03	0.36	0.0
7	Phoning → looking through windshield	0.46	0.09	0.38	0.01	**0.92**	0.02	0.54	0.01
8	Looking through windshield → drinking	0.18	0.24	0.54	0.06	0.27	0.07	0.54	0.0
9	Looking through windshield → looking at backseats	0.05	0.08	0.1	**0.86**	0.1	**0.98**	0.18	0.16
10	Looking through windshield → open middle storage compartment	0.06	**0.83**	0.66	0.19	0.5	0.45	0.66	**0.88**
11	Looking at backseats → turn back and close eyes	0.04	0.21	0.09	0.16	0.07	**1.11**	0.07	0.2
12	Search a pen in the middle storage compartment	0.06	0.01	0.08	**0.81**	0.19	0.04	0.21	0.17
13	Turn around to left back door	**1.38**	0.01	0.61	0.06	0.06	0.04	0.14	1.0
14	Looking through windshield → take photos with smartphone	-	-	0.13	0.9	0.21	0.1	0.53	0.13