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Transparent internal human-machine interfaces in highly automated shuttles to support the communication of minimal risk maneuvers to the passengers

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ABSTRACT

In Highly Automated Vehicles (HAVs) without operators on-board, user interaction with the vehicle automation plays an important role for a safe and inclusive use of these services. Especially when Minimal Risk Maneuvers (MRM) are performed by the system, passengers are faced with uncertain situations. A possibility to deepen passenger's understanding and predictability of these systems and reduce their uncertainties is to enhance automation transparency. However, literature shows a lack regarding enhancing system transparency of HAVs during MRMs. Therefore, we investigated the impact of "observability" and "reasoning" as transparency influencing factors. In an online study, participants evaluated multiple internal Human-Machine Interfaces (iHMI) as shuttle passengers. The presented iHMIs varied regarding their level of transparency by giving different information about what the vehicle's "perception" and its "reasoning" is. Results show significant differences in the passengers' understanding between different iHMI variants providing evidence that information regarding the "perception" and "reasoning" of HAVs enhance system transparency. Results of the study may provide first insights into passengers' informational needs when using HAV. They highlight the potential benefits of system transparency when designing interfaces for HMIs of automated vehicles.

1. Introduction

Vehicle automation in future urban traffic is associated with several possible benefits, e.g., increased traffic safety (Chan, 2017), lower emissions due to a more efficient traffic flow, and inclusiveness of new mobility solutions (Milakis et al., 2017). Although promising, there are still challenges that might prevent vehicle automation from general adoption. Highly automated vehicles (HAV; SAE L4, Society of Automotive Engineers, 2021) often struggle in unknown situations because the automation's intelligent algorithms (AI) lack them in their training data (Zhang, 2020). The algorithms that are commonly used for automated driving systems (ADS) are trained with datasets that incorporate sets of situations. Going on from these, the algorithms learn to recognize these situations and behave according to certain rules connected to these sets of situations. If new situations deviate too much from these training data sets, the AI might not be able to allocate the right behavior to that situation and is unable to continue with the task execution (e.g. the driving task). Hypothetically, a way to solve this, is to include all of the possible situations an HAV can encounter during its task execution and allocate them to sets. Then the proper behavior can be connected to the sets and all situations would be solvable. But,

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since the number of possible situations that can be encountered is likely infinite, this might be unachievable. Additionally, there is no way of knowing if all possibilities are accounted for in the training dataset of an algorithm. This problem is commonly referred to as the "Unknowable Unknowns Problem" (Koopman and Wagner, 2017). Since it might be impossible to engineer a flawless AI that is capable of solving every situation completely on its own, another solution might be more feasible that does not rely on a perfect system but human support instead (Holton, 2023).

Instead of trying to develop a flawless system, a human operator can be incorporated into the automation system via remote operation (RO) to support and assist the ADS in these unknown situations. This may add the human ability to creatively solve problems into the ADS and help support it when no appropriate behavior can be allocated to a situation. Operators can assess situations that are causing problems for the ADS and provide guidance and assistance for the system (Kettwich et al., 2021; Zhang et al., 2021). Additionally, operators can anticipate future situations and problems therein that might be encountered by the ADS (Mutzenich et al., 2021). And since operators can support the ADS from a distance and support multiple vehicles, they are unlikely to compromise the efficiency of automation systems. So, the problem of "Unknowable Unknowns" may be solved using RO as a supportive fall-back position that assists in these unknown situations.

As a result of utilizing the concept of RO, new and uncertain situations for passengers may occur. They no longer see a driver steering the vehicle who is approachable and observable while executing the driving task, even when in fact a human operator is supporting the system, i.e. during minimal risk maneuvers (MRM), which is the transition of an automated vehicle into a stable condition when the given trip cannot be continued safely (Jong Min et al., 2021). The vehicle may spontaneously stop when it reaches unknown situations and performs an MRM, to maximize security during that situation. The RO that would then support the ADS might also not be available to reassure them if passengers experience uncertainty or anxiety due to a situation that might be hard to anticipate. This leads to new requirements in the design of internal human-machine interfaces (iHMI). They should not just account for general informational needs but include specific information about the ADS, the AI and the RO of the HAV (Cysneiros and Raffi, 2018). A possible approach to identify the relevant information that should be given to the passengers is the concept of "transparency" or "system transparency" (Oliveira et al., 2020; Selkowitz et al., 2017). This approach is common in the field of explainable AI (XAI), a new direction of AI development that aims at creating algorithms and automation technology that is explainable to their users (Zednik and Boelsen, 2022). In that sense, system transparency tries to make understanding and predictability of AI and automation systems more attainable by giving information on how a system works and why it makes decisions the way it does (Chen et al., 2014; Mercado et al., 2016). This may also be suitable for HAV since their systems incorporate AI and share basic functionality principles.

In summary, RO can be an important technology for HAV (SAE L4) adoption as it may solve the "Unknowable Unknowns Problem" in the ADS's AI. In order to efficiently use RO research in several areas is needed. One of these areas is how RO can be incorporated into the AI-based ADS and what needs passengers of HAVs have in information and transparency especially during MRMs. To shed light on this we investigate further into the following question.

RQ: "*Does transparency of the passenger communication through an iHMI improve the passengers' understanding and predictability during MRMs*?"

1.1. Remote operation

Remote operation for highly automated driving can be defined as the execution of the driving task from a distance. This execution can take place in different manners, depending on the amount of tasks that are executed by the human operator or the ADS (Shi and Frey, 2021). For example, in remote driving up to the complete driving task can be performed by a human operator. In remote assistance, almost the complete driving task is performed by the automation which leaves only handling MRM to the operator. That means that the main driving tasks are executed by the vehicle's ADS, while the remote operator only intervenes in situations outside the ADS's operational design domain (ODD). Because of this sporadic intervention, one operator might be capable of supporting multiple vehicles, since he does not have to permanently supervise them (Zhang, 2020). As a result of this multi-vehicle support, scalability and therefore efficiency of the vehicle automation may greatly increase. So, task division is likely a feasible and efficient way to support the development of HAV.

The main benefit of the remote operation as part of the automation system is the additional reliability and adaptability, potentially increasing the feasibility of the adoption of HAV in an earlier stage. Different from the AI algorithms of the ADS, human users can adapt more quickly to new situations and find creative solutions to resolve them. A promising way to support the ADS is by giving waypoints that help in solving MRM situations (Kettwich et al., 2022; Schrank et al., 2024). This could also mean that the RO would have to override general traffic rules which are inevitable for the automation, e.g. crossing a lane marking.

To adopt RO as a support for HAV's ADS, system design (Zhang, 2020), possible or necessary roles in remotely operated systems (Schrank and Kettwich, 2021), as well as specific use cases, where remote operation is feasible need further exploration. For example, a remote operator can either remotely drive or assist an HAV which already provides two different sets of requirements for a RO-workplace (2021). According to these varying tasks, different Human-Machine Interfaces (HMI) should be utilized to accommodate different needs of remote personnel during that tasks (Kettwich et al., 2021; Penin et al., 2000; Shi and Frey, 2021). In all of the use-cases for RO the human operator is a vital factor influencing not only the effectiveness of the HAV's automation and the driving performance but passengers' experience as well (Chen et al., 2007; Cooke, 2006; Liu et al., 2017). Though the tasks and influencing factors differ between the use-cases of RO, the human support is likely feasible in all of them.

The black-box problem is an additional challenge with integration of modern AI algorithms in ADS (Zednik, 2021). It applies to any area, where human users interact with an automation system that incorporates complex AI algorithms to support decision making or task execution. The black box problem originates in the complexity of modern ML algorithms commonly used in AI. These algorithms have become so complex, that even developers struggle to understand their functioning and as a result cannot explain why an algorithm reached a certain conclusion (Adadi and Berrada, 2018). So, when an AI is being incorporated in a system like HAV and RO, it is important to know how deep of an understanding is needed by a user to navigate a system and predict its behavior, and thus how this understanding and predictability can be reached. So, in order to realize remotely operated HAVs, there might be a need for more understandable AI (XAI) that is more explainable in general and also to users and passengers of automated vehicles (Atakishiyev et al., 2021; Kuznietsov et al., 2024).

1.2. Communication with shuttle passengers

The remote assistance of HAV can be defined as a socio-technical system where operators support an ADS that is supported by AI algorithms. This system presents a completely unknown situation for passengers. Not only would they experience a vehicle without a visible driver. They would also face situations in which the ADS may behave in unknown ways, like MRMs. In these the ADS would stop if it encounters a situation unknown to its algorithms. Passengers might experience this as unreasonable behavior, and require that an explanation for the behavior is presented to them or generally available in the iHMI. If this is not the case, passengers could experience uncertainty towards the HAV and its behavior because they would not be aware of what is happening and what is going to happen in the near future (Cummings et al., 2020; Meurer et al., 2020). The iHMI, which communicates information to passengers, should take these uncertainties into account by giving adequate information to them through providing explanations about the MRM. In case of machine to human communication not any sort of information might be suitable to reduce uncertainty and insecurity (Mercado et al., 2016).

In addition, the AI commonly used in ADS and other technologies have become increasingly complex (Rahwan et al., 2022; Zednik, 2021). This may increase the effect on uncertainty towards the reasoning of the ADS and increase unpredictability, as it is often unclear how a conclusion has been reached by the algorithm (Dahl, 2018). On that account, the field of XAI has emerged in AI development in order to provide human-understandable explanations of how an algorithm or automation technology works. This might be achieved by including information in the HMI that provides transparency of the ADS and its AI (Eschenbach, 2021). That means that provision of explanations and transparency information may help with passengers' uncertainty towards MRMs in HAV and the ADS' predictability.

1.3. Transparency of technology

Transparency, which provides information about a system's actions and its reasoning behind its actions, could help achieve more understandable ADS during MRMs while using HAV (Chen et al., 2014; Selkowitz et al., 2017). Previous research has shown that transparency can increase trust, understanding and predictability and subjective safety (Oliveira et al., 2020). Therefore, the main goal of the proposed interaction strategy is to increase passengers' understanding and the predictability of the HAV's behavior during MRMs by enhancing the transparency of the ADS. Information increasing transparency can range from consecutively displaying vehicle status to giving examples for a system's reasoning and much more. The goal of all of these is to give information that is able to explain the system's behavior in specific ways. It can be example-based (Cai et al., 2019) or regarding the AI's reasoning and decision making (Huff Jr et al., 2021). XAI for example, focuses on how explanations can help in understanding the functioning of AI algorithms. The amount of transparency that can be reached using certain explanations can be separated into levels (Chen et al., 2014). These levels indicate the depth of transparency and as a result the depth of understanding that is expected to result from the explanation. Firstly, information about "What" the system is doing can be shown in an interface (Vorm & Combs, 2022). For example, system state and current system behavior (e.g., "driving mode") can be shown in the interface to increase level 1 transparency. In a next step, the reasoning behind the behavior can also be incorporated (Chen et al., 2014). Though this should increase level 2 transparency, explaining the reasoning behind and AI algorithm can be complicated. As discussed, examples are a possibility to easier comprehend the reasoning of an AI. That could be a categorization for what the vehicle sees, e.g. a box with a label surrounding pedestrians in the camera view, to show what the algorithm recognizes or thinks it is recognizing. In order to further increase transparency, the algorithm's planning might be depicted. An example to incorporate this into an interface, would be to incorporate trajectories in the camera perspective of the vehicle. This would show operators, where the vehicle is planning to go. A vehicle's reasoning can differ wildly and as a result, explanations can be challenging to incorporate into the system. So, it poses a challenge to find the relevant information that is likely to increase transparency in an HAV to increase passengers' understanding and the predictability of the system.

1.4. Hypothesis

Until ADS technology has advanced into flawless or at least fail-safe systems (Lee et al., 2022), providing a safe and reliable fallback system in case of system malfunction or performance degradation, MRM situations will occur frequently. As MRM provide uncertainty and unpredictability for passengers, it may be important to support passengers' experience when using HAV. The main goal of the interaction strategy is to increase trust, understanding and predictability into the vehicle automation by enhancing the transparency of the automation. Especially in situations with a high user-uncertainty (e.g., an MRM), enhanced system transparency should power passengers' understanding and predictability of the HAV's behavior and subsequently make the ride more enjoyable and raise acceptance and usage of HAV. This leads to the hypothesis that:

H1: "Higher levels of transparency increase passengers' understanding and predictability in HAVs behavior during MRM."

We assume that subjective usability is also influenced by the amount of displayed information on an interface. Since the amount of information increases with the different levels of transparency, usability might also be affected. Since the specific impact of the additional information with increasing levels of transparency on usability is unclear, this was an important research question of the present study. As a result, we want to provide insight into a positive (e.g., enhanced usability) or negative effects (e.g., overload in information that might overwhelm passengers). Transparency might only enhance user experience when the information that provides transparency actually support an actual need. Unnecessary information or too much information might impede user experience rather than enhancing it counteracting the main goal of this research. However, we assume that there might be an influence of transparency information on passenger's experience resulting in the second hypothesis.

H2: "The subjective usability of the interface variants is influenced by the amount of transparency in the depictions."

MRMs may provide a situation with a high degree of uncertainty for passengers of HAV. This uncertainty is caused by the presumed inability of passengers to easily comprehend these types of situations and anticipate their development due to the ADS' complexity. This uncertainty may further increase with situational factors important to passengers. We assume that time pressure could be an important factor in passengers' evaluation of the HMI, resulting in differences in their evaluation regarding the importance of informational needs. We therefore investigated the effect of an exemplifying context factor in the third hypothesis:

H3: "The evaluations of the importance of HMI-information is different when time pressure is added into the situation."

2. Materials and methods

2.1. Sample

An experimental online-study with a total of N = 49 (female = 19, male = 30) participants was conducted. The participants were recruited via the DLR sample pool of interested people, social media (LinkedIn, Twitter) and private networks. Participant's age ranged between 20 and 69 years ($M = 35.65$; $SD = 13.67$) and their technical affinity (Franke et al., 2019) was around $M = 4.37$ ($SD = 1.11$) on a scale of one (min) to six (max). All of the participants were required to be at least eighteen years old and speak fluent German. They also had to have a valid driver's license. The annual distance driven ranged from 500 to 30000 km ($MW = 10300$; $SD = 10245$). The participants were not compensated but were incentivized by a raffle where they could win one of four vouchers valuing 25.- Euro each.

2.2. Study design

The online-study was designed as a single within-factors design containing five factor levels with repeated measures regarding understanding and predictability, as well as perceived usability (see 2.3 Materials). Thus, every participant experienced every of the five interface designs. The order of presentation of the five designs was randomized using urn drawing implemented into the website's code automatically assigning an individual order of presentation for each participant. After every interface variant the participants had to answer questionnaires regarding their understanding, perceived predictability, and their subjective usability. The study was conducted using SoSci-Survey, an online tool for Sociological and Psychological studies (Leiner, 2024).

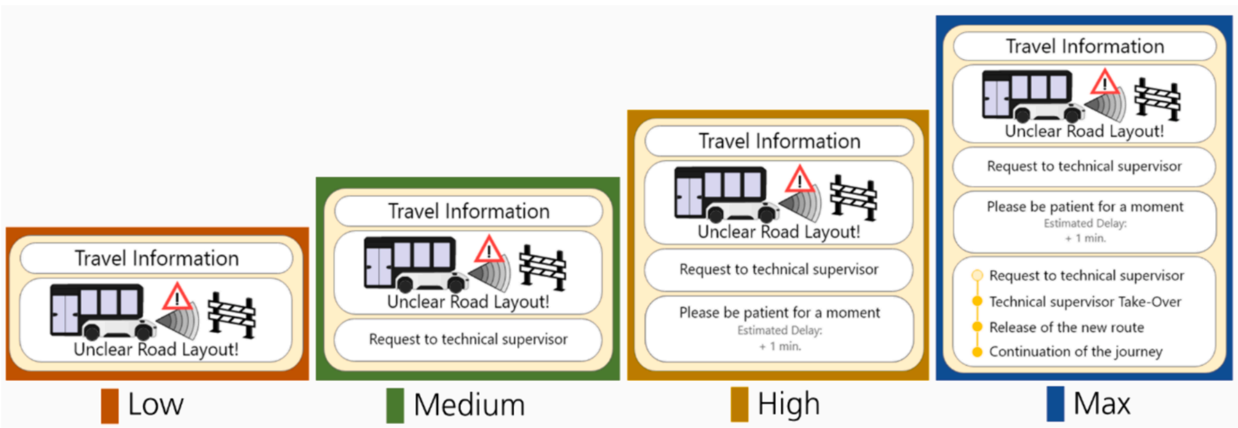

Fig. 1. Different levels of transparency with the provided information conveyed by the iHMI.

2.3. Design of an internal Human-Machine Interfaces (iHMI)

Following the guidelines to develop and implement an iHMI that were presented previously, information for different levels of transparency are necessary to inform passengers of HAVs during MRMs. Providing them with this information may increase transparency and result in higher understanding and predictability of the system and help reduce anxiety and uncertainty while using these mobility systems. We designed variants of an interface trying to follow these guidelines. The variants differed in their amount of information to increase the level of transparency (see Fig. 1). In a first step, the interface did not display any additional information to increase transparency while the HAV performs an MRM. This variant functioned as a baseline to see if the addition of transparency would indeed increase understanding and predictability (Fig. 2). Then, on the first level of transparency, information about "what" caused vehicle's performance of the MRM was added as a pictogram with additional text "Obstacle detected". In a next step, the amount of information was increased presented by adding the current step of the RO support to the existing information. This was done by adding a simple field of text prompting "Sent request to technical assistance.". The second highest level of transparency added information about the expected delay time to the existing information further enrichening the information. This provided passengers with information about the consequence of the MRM. In this level of transparency, the complete amount of "what" happens and "why" it happens was displayed to the passengers. The final level of transparency added information about the next steps of the remote operation support, by adding a process bar stating what steps are next in the process of resolving the MRM (Fig. 3). So, in the deepest level of transparency information about what caused the MRM, what consequence that has to the travel time and the current and future steps in the remote support were presented to the passengers of the fictional HAV.

2.4. Questionnaires

To investigate the passengers' evaluation of the iHMI, questionnaires regarding their understanding and perceived predictability, their subjective usability as well as reported importance of elements were conducted.

2.4.1. Understanding

In order to concisely survey participants' understanding, it was operationalized using the "understanding and predictability" subscale of the trust in automation questionnaire by Körber and Gleissl (2022). The questionnaire was designed to measure trust in automation using a definition of trust that incorporates not just the propensity to trust, but also the understanding of the automation, as well as the attitude toward the automation's developers. This fits well with the definition of passengers' understanding and trust that was earlier presumed to be a result of higher levels of transparency. Thus, this study used the subscale "understanding and predictability", which consists of four items regarding the user's understanding and subjective predictability of the system (i.e., "It's difficult to identify what the system will do next."). The internal consistency index omega (ω) total was reported as $\omega = 0.81$ for this subscale (Körber, 2019). The subscale was chosen because of its concise nature and the general quality of the questionnaire, regarding validity and reliability (Gold et al., 2015; Kohn et al., 2021; Körber, 2019).

Fig. 2. Picture shown to participants illustrating the MRM with a base version of the HMI.

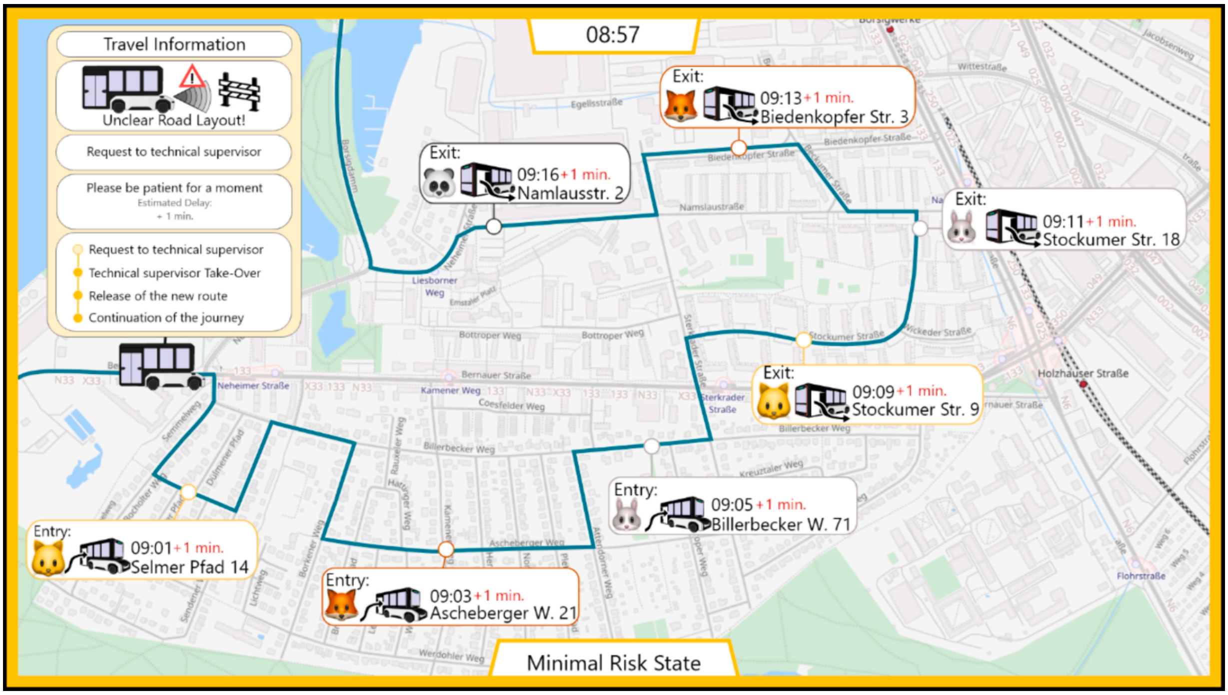

Fig. 3. The interface with the highest level of transparency shown during the MRM.

2.4.2. Usability

In addition to passengers' understanding and predictability participants' subjective usability was measured as well using the user experience questionnaire in its short version (Schrepp et al., 2017). The UEQ-S consists of two subscales, the "pragmatic" and the "hedonic". The hedonic subscale focuses on an interface's appeal. The pragmatic subscale focuses on the usability and informational accessibility of an interface. For this study we used primarily the "pragmatic" subscale (Schrepp et al., 2017), which consists of four items and measures the subjective evaluation of the interface's usability. The Cronbach Alpha values of the pragmatic quality ($\alpha = 0.85$) and hedonic quality ($\alpha = 0.81$) scales, measuring internal consistency, were reported as reasonably high (Schrepp et al. 2017). To evaluate an interface the questionnaire uses two-point scales with two-point value-pairs (i.e. "efficient-inefficient" for pragmatic, "boring-exciting" for hedonic). In addition to the use of the subscale to evaluate the different levels of transparency, the whole interface was also examined using both scales.

2.4.3. Influencing factors on HMI evaluation

In addition, different parts of the interface were evaluated using a set of questions evaluating the importance of these parts on a scale of one (not important at all) to seven (very important). The participants rated different elements of the HMI (the orange frame of the interface during MRMs, the cyano-colored frame during automated driving, the symbol for the obstacle detection, the prompt declaring the request toward the RO, the expected delay time, the sequence diagram regarding the ROn, the position of the own entrance and exit on the map, the position of other passengers exits on the map, the current time, the time of the own entrance as well as the time of the own exit) on a seven-point likert-scale (from 1 = not important at all to 7 = very important). The participant's task was to evaluate "Please evaluate how important the following parts of the interface are for you, in the case of a minimal risk maneuver.".

Additionally, the interface parts were evaluated under time pressure to evaluate an additional influencing factors on HMI evaluation. Time pressure was added by complementing to the original instruction "Under the pretense that you are late for an appointment.".

2.5. Procedure

The participants reached the homepage "SoSci-Survey" via Link that was shared on social media and among private social-groups. Additionally, members of the DLR sample pool could reach the online-study via the sample pool site (SONA). First the participants had to answer questions regarding their demographics. They were then instructed to imagine themselves on board of an HAV driving through Berlin Tegel to visit a friend during the whole time of the study. To support the imagination, a picture of the vehicle was shown to them. They then had to imagine that the HAV performed an MRM in front of a car blocking the road. They were provided with a picture of the scene to support their imagination (see Fig. 2). Next, we presented the participants with a picture for each of the different iHMI variants with varying levels of transparency, regarding the MRM and the ROn process, like delay time and cause for the MRM (see

Fig. 3). They could look at the HMI as long as they liked and continue when they were ready to do so. The design of the iHMI aimed to increase transparency of the iHMI and as a result increase passenger's understanding and predictability of the system. The iHMI was map-based and depicted a route including destinations of the participants and additional fictitious passengers. The destination information was coded to different passengers using animal-like emojis which were depicted inside pop-up windows. The pop-up windows marked entries of other passengers, the exits of the participants as well as the hypothetical other passengers (see Fig. 2). A separate popup window within the map-based interface incorporated additional information about the MRMs as part of the iHMI (Fig. 1). The pop-up windows were also coded with a pictogram of the shuttle to mark the current position of the shuttle. This also indicated the place where the MRM would have occurred on the route. After each variant, the participants had to answer eight questions regarding their understanding, predictability and perceived usability. They had no time limit to answer the questions and could continue on their own time. After evaluating each variant of the iHMI the participants were tasked with evaluating the usability of the interface as a whole, first without time pressure, then with time pressure. Time pressure was induced via a vignette description, where they had to imagine being late for a work meeting. After the vignette they were asked to evaluate the interface parts again (see 2.4.3).

3. Results

Inner-subject effects were calculated using repeated measures ANOVA for *Understanding and Predictability* and *Usability* with Bonferroni adjusted post-hoc tests. Sphericity was checked using Mauchly's test for sphericity ($p < 0.01$) and corrected using Greenhouse-Geisser adjustment (Field, 2018). According to Shapiro-Wilk test all but one group were normal distributed which was not adjusted for, since RM-ANOVA are resilient to violations and N was > 40 (Berkovits et al., 2000). Effect sizes were calculated as Omega square ($\ddot{\omega}^2$: Small effect = 0.01, Medium effect = 0.06, Large effect = 0.14; (Lakens, 2013). Results were analyzed using Excel and SPSS Statistics by IBM.

3.1. *Understanding and predictability*

In hypothesis one the influence of the different transparency levels of the HMI on passengers' understanding and predictability was investigated. Results show descriptively higher average values for passengers' understanding in higher levels of transparency. The increases also come with reduced standard deviations for conditions with transparent iHMI design (Table 1). Results in subjective understanding and predictability range between 2.78 ($SD = 1.14$) for the condition without additional transparency towards the MRM and 4.13 (SD=0.82) for the highest amount of transparency.

The results also show that improvements in user understanding and predictability with higher levels of information are significant for a repeated measures ANOVA with a Greenhouse-Geisser correction, $F(2.77, 133.11) = 22.51$, $p = 0 < .001$, $\ddot{\omega}^2 = 0{,}303$. From "No information" given to the highest level of information richness, understanding and predictability scores improved significantly in a Bonferroni-adjusted post-hoc analysis ($p = 0 < .001$; $M_{\text{Diff}} = 1.35$, 95 %-Confidence Interval [0.75, 1.94]). This further supports the hypothesis that transparency can in fact improve passengers' understanding and predictability of HAVs during MRMs. Differences between "No" and all other amounts of transparency show significant differences (see Fig. 4). Differences between "Low" and "High" levels of transparency improve significant, as well as between "Med" and "Max" levels of transparency, further supporting the investigated hypothesis. Only differences between directly adjacent levels of transparency like between "High" and "Max" levels of transparency show no significant differences, with the exclusion of the difference between "No" and "Low" transparency, which also improves significantly.

3.2. *Usability*

Regarding H2 that subjective usability is influenced by the amount of transparency, the results of the usability questionnaire ranged from $M = 4.29$ ($SD = 1.64$) for the low level of "No transparency" to M=5.16 (SD=1.45) for the information level of "High transparency" (Table 2).

An ANOVA for repeated measures with a Greenhouse-Geisser correction revealed significant differences regarding usability between the variants for, $F(2.63, 125.98) = 5.20$, $p = 0.003$, $\ddot{\omega}^2 = 0.08$. Using a Bonferroni-adjusted post-hoc analysis, only the differences between "No Information" and "High Information" showed significant differences ($p = 0.013$; $M_{\text{Diff}} = 0.88$, 95 %-Confidence

Table 1
Descriptive statistics for user understanding and predictability across the levels of transparency.

Understanding and predictability	M	SD	SE	95 %-CI	
				Lower	Upper
No Info	2.78	1.14	0.16	2.45	3.11
Low Info	3.39	0.85	0.12	3.15	3.64
Med Info	3.56	0.84	0.12	3.32	3.80
High Info	3.86	0.0.79	0.11	3.64	4.09
Max Info	4.13	0.82	0.12	3.89	4.37

M = Mean, SD = Standard Deviation, SE = Standard Error, 95 %-CI = Confidence Interval.

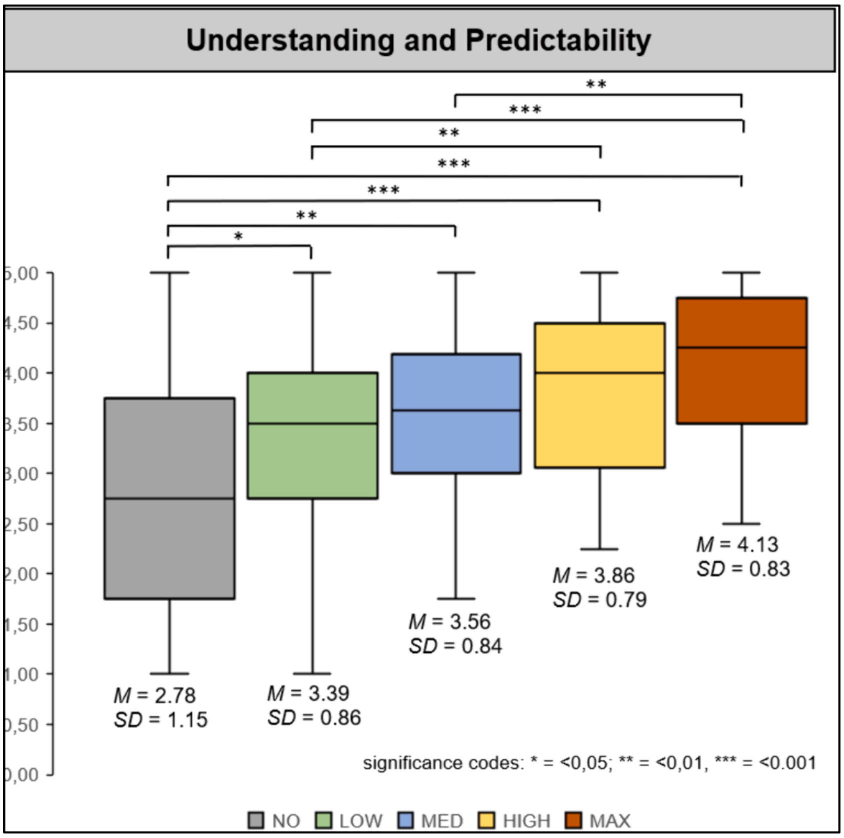

Fig. 4. Median understanding and predictability for the different levels of transparency with min/max and highlighting of significant differences between HMI variants.

Table 2
Descriptive statistic for usability across the levels of transparency.

Usability	M	SD	SE	95 %-CI	
				Lower	Upper
No Info	4.29	1.64	0.23	3.81	4.76
Low Info	4.91	1.49	0.21	4.49	5.34
Med Info	4.79	1.52	0.22	4.35	5.23
High Info	5.16	1.45	0.21	4.75	5.58
Max Info	5.06	1.59	0.23	4.60	5.51

M = Mean, SD = Standard Deviation, SE = Standard Error, 95 %-CI = Confidence Interval.

Interval [.12, 1.63]). Thus, the results do not completely support the hypothesis that different levels of transparency influence usability of an HMI in HAVs during MRMs.

3.3. Influence of time pressure on interface evaluation

In addition to the questionnaires regarding usability and understanding and predictability, the evaluation of the importance of different parts of the HMI depending on time pressure was evaluated (Fig. 5). The results regarding the associate hypothesis (H3) show differences in evaluation of the interface under time pressure. Of these differences the current time ($p = 0<.001$; $M_{\mathrm{Diff}} = -0.61$, 95 %-Confidence Interval [−0.89, −0.34]), expected time of arrival ($p = 0.001$; $M_{\mathrm{Diff}} = -0.55$, 95 %-Confidence Interval [−0.86, −0.24]) and the time of expected delay ($p = 0<.05$; $M_{\mathrm{Diff}} = -0.24$, 95 %-Confidence Interval [−0.46, −0.03]) were significant. The differences support the hypothesis that time pressure as a potential factor does affect passengers' evaluation of different parts of the interface. Additionally, information regarding the position of the own exit and the position of other passengers on the map were regarded as less important. These differences were statistically not significant.

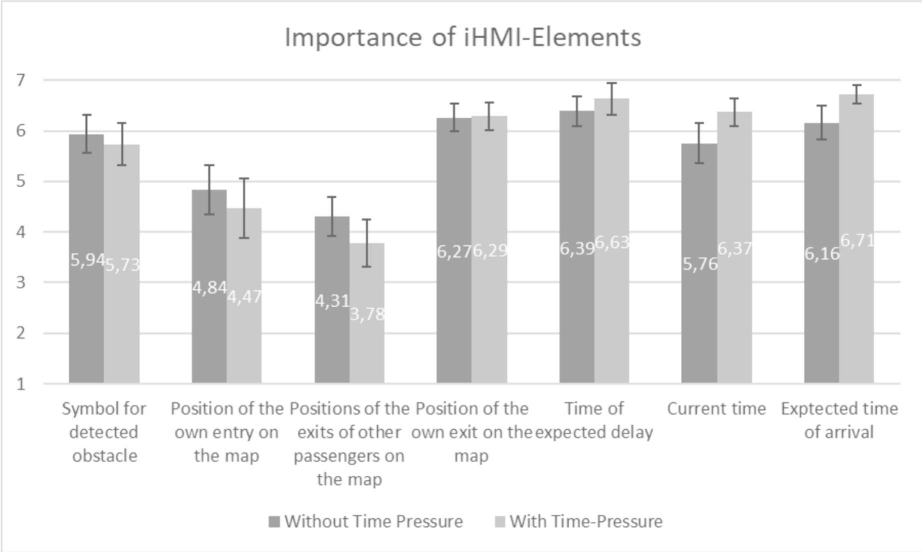

Fig. 5. Reported subjective mean importance of specific interface parts with and without time pressure including 95%-CI.

4. Discussion

We investigated the influence of different levels of transparency information on passengers' subjective understanding, predictability and their subjective usability and how time pressure as a potential influencing factor affected the evaluation of different interface parts. Though the scope of the study was limited to the most important concepts, results indicate support for two of the hypotheses.

4.1. Understanding and predictability

For the different variants of the iHMI the results of the subjective understanding and predictability questionnaires show mixed results. Participants reported higher subjective understanding with increasing levels of iHMI transparency. Thus, H1 can be accepted and it can be assumed that increasing transparency levels increase passengers' understanding and predictability in the ADS during MRMs. The variants of the interface incorporated information with increasing levels of transparency towards the ADS and the RO and thus increasing transparency. This resulted in significantly higher values of passengers' understanding and predictability for each step of increase in transparency information. Though the increases were not significant in each of them, we assume that overall the increases might be linear (see: Fig. 4). The biggest difference in adjacent steps was observed between "No Information" and "Low Information" given. This suggests that the initial reasoning of the HAV can be regarded as an important step to improve passengers' understanding and predictability. Giving no additional information about the ADS's current state and reasoning left passengers with lesser values in understanding and predictability. Though the addition of the current process of the teleoperation, as in the highest level of transparency information ("Max Information") shows higher values in understanding and predictability, the rise is not significant to results in "High Information" and might not contribute as much value as the information about the ADS's reasoning. This might indicate that information about the process of the teleoperation either does not add to passengers' understanding or not at the beginning of an MRM. The information about the time delay in the variant "High Information" added to the understanding of passengers and might be a more important information. This could be the case, if there is indeed an orientation happening that needs time to resolve until further transparency information can add to passengers' understanding and predictability. What process contributed to this and if a need for orientation is influenced by higher degrees of transparency is unclear and discussed in literature (van de Merwe et al., 2024). If the positive effect on understanding could also contribute to the automation induced fallacies as described in the ironies of automation is unclear, too (Bainbridge, 1983). As described, less interaction with a task can lead to a lack in knowledge and experience. For example, this could contribute to the uncertainty experienced by passengers in completely new situations, as they lack knowledge or experience of similar ones. What remains unclear as well is the occurrence of overload in this study. The amount of information that increased with each level of transparency did not reach a point were understanding and predictability appeared impeded. Cognitive impairment as a result of information overload is commonly expectable, when increasing amounts of information are given (Bawden and Robinson, 2014). Since this was not clearly observable in this study, information might not have been overwhelming or the situation itself lacked an amount of complexity qualified to overwhelm participants (Park et al., 2022). This might also be supported by the results regarding usability.

4.2. Usability

Usability was rated with above scale mean values in each level of transparency information and thus rated relatively high. Though the repeated measures ANOVA investigating the influence of transparency on usability was significant, we cannot assume that there was in fact an influence. Results in usability increased with the levels of transparency information but post-hoc tests revealed that only in one condition usability was significantly higher. The other differences can best be described as inconclusive, since they show no systematic influence. Thus, the influence of higher transparency was at best positive and appears to have not reached an amount of information overload. This is somewhat surprising since the interface contained a lot of information regarding the trip, as well as additional information regarding the MRM and RO to increase transparency, which could have likely been cause for information overload, which could have resulted in lower usability of the system (Khairat et al., 2019). Usability did not show higher results regarding the interface with the most transparency information as could be expected with availability of more transparency information. This may hint towards an overload in information. Since the information did not appear to negatively impact usability, we might also assume that not all of the information regarding transparency was regarded as relevant by the participants. Redundant information in the interface could have been ignored by passengers and as a result not caused a drop in perceived usability (Bawden and Robinson, 2014). An alternative conclusion may be that the depiction of information did not confuse the passengers and did not hinder their information gathering (Bawden and Robinson, 2014). The information bits that were integrated in the interface were focused in areas where they were most important, instead of being scattered among the interface which would have likely obstructed their availability since it forces users to jump between the information bits (Conti et al., 2006). Additionally, scattered depiction of information would have provided no context for the information itself and further decreased usability. If this in fact provided the interface with better usability cannot be answered in this paper, but was considered during interface design. What can be said with some certainty is that usability was not significantly impaired by the additional information in the different levels of transparency.

4.3. HMI evaluation with time pressure

In addition to the evaluation of different levels of transparency information in the iHMI we investigated the importance of specific information of the interface with and without time pressure (H3). Under time pressure information regarding current and delay time, were regarded significantly more important than without time pressure. The shift in evaluation can well be explained with a focus on the information that is regarded most relevant to the passengers in the current situation (Mynatt et al., 1993). If an information is directly linked to it, it is therefore more important for the passenger. Interestingly, though this is established for task execution (Brass and von Cramon, 2004), it appears to be similar when tasks are automatically executed. Though the information that are relevant for the execution of the task itself might be less important and the focus shifts towards the relevant result, linked to the task. At the same time other parts of the interface were regarded as less important. This may point toward a limit of attention or subjective importance. This could indicate that passengers can only regard a limited amount of information in an interface as relevant, depending on the specific situation. This may point to a connection to limited cognitive resources as are commonly referred to in task execution (Oulasvirta et al., 2005).

4.4. Limitations

Results of this study provide insights in the design of iHMI for transparent communication with passengers of HAVs during MRMs. The results suggest that understanding and predictability significantly improves with higher levels of transparency information regarding the ADS and the RO. This might mean that their informative value is highest regarding this specific setting. So, the explanatory value may be limited to the context of RO of HAV-shuttles as well as a graphical iHMI like the one considered in this study. Nonetheless, HMI transparency is a promising proposition for adoption in many different fields as well (Bitzer et al., 2021; Detjen et al., 2021; Kilgore and Voshell, 2014). Furthermore, the differences between the interface variants could have been overestimated due to the within-subject design of the experiment. As the participants were asked to rate every of the five transparency levels, they might have been aware of the experimental manipulation and the research purpose (Charness et al., 2012).

Additionally, the direct influence of understanding and predictability on trust was not investigated. The influence of understanding, often proposed in literature, can be explained by the collaborative task execution of users that need an understanding of when the automation can safely be used, for example in SAE L2 vehicles (Hancock et al., 2019). In HAV (SAE L4), especially shuttles, users are not necessarily expected to execute any part of the driving task. This may affect the effect of understanding on trust in a way that no understanding is necessary to develop trust. In that case, trust could instead be based on experience (Hoff and Bashir, 2015) and trust in the developers of the used vehicles (Körber, 2019). If this is the case, it should also be the investigated in future research as it was outside of the scope of this study.

Another limitation is the number of investigated scenarios. The findings in this study were only evaluated in a single scenario. Therefore, the results are limited to that scenario and might not apply to any given situation that HAV passengers might find themselves in. Since the number of possible scenarios might be unlimited, more of them should be investigated to validate the design criteria for transparent interfaces and their adaptability. This is further increased as results also point towards informational needs maybe being more specific to situations and some additional parameters that were not investigated in this study.

The study was also conducted as an online study leading to further limitations in its external validity. Participants were instructed to imagine themselves as passengers, which is a viable way of conducting research in this direction (Murphy, 2022), but its expressiveness might be limited. To increase the validity, more realistic methods, like simulations or real-life experiments, which provide better immersion and interaction possibilities, might be more suited. Nevertheless, the results of this study provide insights that might be used as a valid starting point for future research and iHMI design.

5. Conclusion

The present study provides evidence that transparency of an iHMI giving additional information about ADS's behavior during MRMs positively influences passengers' understanding and predictability. Higher levels of transparency information show significantly better passengers' understanding and predictability than lower levels of transparency information. This effect appears to increase with the depth of transparency given by the information, which points to a systematic effect. However, the specific level of transparency that shows an ideal compromise is still unclear and needs further investigation. With transparency in mind interfaces may be designed in a more understandable way, even for more complicated systems utilizing AI algorithms. Consequently, this may also improve passengers' trust and experience in these new and unfamiliar transportation services like HAV. This is also supported by the unaffectedness of the system's usability seen in this study. Usability appears to remain relatively stable by the additional information providing higher levels of transparency. Since transparency did not significantly impair usability it seems feasible to implement this principle into the design of ADS and remotely operated HAV. If information overload would occur at some point remains unclear and needs further investigation. Results indicate that there may be an effect on usability in higher information levels. Results also point towards different informational needs specific to context and situations. Therefore, it might be most suitable to not only provide more transparency in the system as a whole, but also include an amount of adaptability towards different situations or types of situations. This may also account for individual needs and provide better inclusivity of the system. Study results clearly indicate that a lack of transparency on the ADS' and RO state could significantly impede passengers' experience and may leave passengers in a state of uncertainty. Consequently, any amount of transparency information increased understanding and predictability, likely improving passengers' experience. This can be utilized by giving information about the system to passengers of HAV, for example about its current state, future states, or the current presence of a remote operator. However, these results need to be validated in real life or simulator studies. Overall, the study's results provide insights into passengers' needs during the use of HAV and highlight the importance of system transparency by being a feasible way to improve passengers' experience even during MRMs. Thus, we propose that system transparency should be considered when designing future interfaces for automated vehicles.

CRediT authorship contribution statement

Thorben Brandt: Writing – original draft, Visualization, Validation, Supervision, Methodology, Formal analysis, Data curation, Conceptualization. **Marc Wilbrink:** Writing – review & editing, Visualization, Software, Methodology, Conceptualization. **Michael Oehl:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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