Adaptive User Experience in the Car—Levels of Adaptivity and Adaptive HMI Design

Lena Rittger, Doreen Engelhardt, and Robert Schwartz

***Abstract*— Advancements in driver state detection and artificial intelligence allow for more and more user-centred and individual experiences. Intelligence and adaptivity in the vehicle context address the three main goals: Increasing safety, usability and empathy in vehicle systems. Adaptivity of systems can be evaluated by considering the technical system features, user-interface-related features and the actual user experience of the adaptive system. We provide an overview of classifications for adaptive systems including the Levels of Adaptive Sensitive Responses (LASR). The levels differentiate the input that a system considers in its operations to adapt to user groups or to the individual user. Along with that, we propose User Experience (UX) design guidelines applicable to the different levels. In an online survey, we varied LASR and one of the UX design guidelines, namely transparency. The within-subjects study showed that both, the levels and the variation of transparency, influenced the perception of intelligence, transparency and intuitive design. However, a significant proportion of users did not understand the difference between the two LASR versions, indicating that users build mental models of systems that imply more personal data usage than the system actually employs. The LASR framework allowed this differentiation to be revealed in system performance and user perception. More research is necessary to elaborate the correlation between levels of adaptivity, UX design, specific UX design guidelines and user experience measures.**

***Index Terms*— Adaptive algorithms, adaptive systems, affective computing, human–computer interaction, intelligent vehicles, interactive systems, road vehicles, user interfaces.**

I. Introduction

THE number and complexity of features in the vehicle is increasing. Carmakers address that by improving the adaptivity of functions to reduce interaction time and with that distraction while driving [1]. Intelligent systems thereby support the maintenance of high levels of driving safety, because they take into account the current context and individual driver behaviour as input parameters for system response [2].

Additionally, structural changes in the automotive industry lead to questions being asked about how customers will be attached and bonded to their car in the future (e.g. considering car sharing rather than owning cars). Focusing on emotional attachment, Braun *et al.* [3] identified different attachment types. They concluded that personal attachment to the car could be grounded in self-empowering reasons, memories with the car, increased status or a loving friendship towards the car. This research emphasizes the need to address individual, personalized experiences in the car. Consequently, interaction with technical systems becomes more and more personal. Similar to a human companion or assistant, an intelligent system supervises users, brings their behaviour, state and needs into context and provides the right assistance in terms of how information is presented and how automatic systems respond [4]. Hence, we believe that from a user experience perspective, adapting systems towards individual user requirements and contexts is the next meaningful step towards full user centricity.

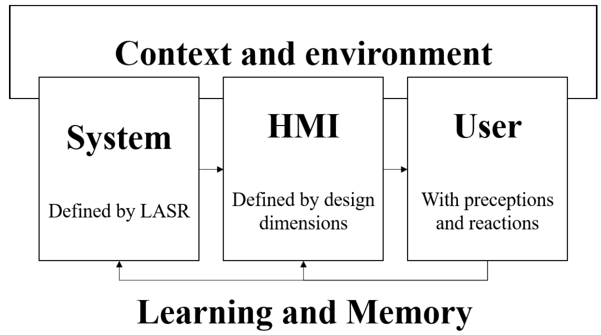

Fig. 1. Relation between system, HMI, and user perception.

We describe this adaptivity of features in the vehicle in terms of three elements based on working models in the context of HMI development [e.g. 5]. First, the technical implementations of the function itself, i.e. the input parameters, algorithms and sensors required to realize the intelligent function. Second, the HMI design in terms of everything that the user experiences of this intelligence and finally the users' perception and reaction to the adaptivity itself. To guide the research focus and to identify potentials for improvement, evaluation and influence on user perception, we believe that a clear understanding of these three elements is necessary. Fig. 1 shows that system, HMI and users interact within a certain context and environment. Adaptivity can be realized by learning and a memory within a shared history.

The goal of the current research is to investigate user experience in response to different types of adaptivity on a system level in interaction with different HMI design realizations.

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This work involved human subjects or animals in its research. The experimental procedure and protocol was evaluated following an ethical evaluation according to national standards. Procedures are internally documented and insight can be granted through first and second author.

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10. The computer decides everything, acts autonomously, ignoring the human
9. …informs the human only if it, the computer, decides to
8. …informs the human only if asked
7. …executes automatically, then necessarily informs the human
6. …allows the human a restricted time to veto before automatic execution
5. …executes that suggestion of the human approves
4. … suggests one alternative
3. …narrows the selection down to few
2. …offers a complete set of decision/action alternatives
1. …offers no assistance, human must take all decisions and actions.

Fig. 2. Automation levels defined by Parasuraman *et al.* [9].

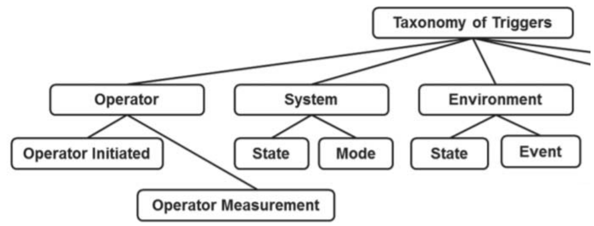

Fig. 3. Examples for triggers of adaptivity by [3].

To this end, the following sections introduce classifications for intelligent, adaptive systems, including the novel LASR (Levels of Adaptive Sensitive Responses) framework [6]. We then introduce the initial implications for HMI design. Subsequently, we report an online study demonstrating the influence of varying LASR and transparency levels on the user's perception of the system. Finally, we conclude with a discussion on the study implications and the demands for future research. With that, this paper contributes to the understanding of system adaptivity and UX design and their effect on the user experience of adaptive vehicle systems.

II. Intelligent Systems

Völkel *et al.* [7] investigated the core aspects of intelligent systems in academic literature by text analysis and concluded that intelligent systems are described by adaptivity and automation. Automation has been defined as "the execution by a machine agent of a function that was previously carried out by a human" [8]. As regards the levels of automation, Parasuraman *et al.* [9] defined automated systems more specifically by taking over different steps of human information processing such as sensory processing, perception, decision-making and response, i.e. either the human or the computer perceives, interprets or performs the respective behaviour. The highest level of automation (level 10) means that the computer decides and acts while ignoring human input (Fig. 2). Due to the fact that the categories are based on human information processing, they limit the description of automated functions to the HMI output part of systems. The technical description of the background for the automation is missing. Conclusions for the HMI output can be drawn in terms of how proactive (system suggests or automatically performs) and transparent (e.g. system informs) the HMI is designed.

In the driving context, the SAE J3016_201806 levels of automation [10] describe which tasks the automated vehicle takes over from the human, e.g. longitudinal control, longitudinal and lateral control or monitoring the environment. The crucial shift occurs when switching between levels two and three, where either the driver or the vehicle has the responsibility for monitoring the driving environment.

Artificial intelligence (AI) research has elaborated on automation procedures for various applications. In particular, Winston [11] emphasized on the role of AI to develop procedures which allow the system to perceive, deduce and act. In order to pave the way for the technical realization of automation, two main objectives have to be met by means of AI: the first is to design technical systems which perform human cognitive operations, and the second is to simulate and model cognitive processes [12]. As will be discussed in the following sections, AI is the technical enabler for adaptive systems.

While the definition of automation focuses on the explanation of which sub-task is performed by the system or the user in the same manner for each user, adaptivity describes that the system does not always react in a single predefined way, but selects reactions differently according to situation and user. Feigh *et al.* [4] defined adaptive systems as "the technological component of joint human-machine systems that can change their behaviour to meet the changing needs of their users, often without explicit instructions from their users. Adaptive systems do so by tracking and sensing information about their users, their current tasks and their environment." With that, the definition of adaptivity allows a focus on the personalization and/or the situation dependency of functions and thus includes some technical background for the realization of intelligent functions. Adaptive systems measure and model the input parameters that initiate and operate the intelligent system. Feigh *et al.* [4] also report different input parameters in terms of triggers. These triggers basically describe different classes of information or input variables that initiate adaptation, e.g. operator, environment, time or location (Fig. 3).

In the car, progress in adaptivity has been made in the context of driver assistance systems, mainly focusing on information needs, workload and safety-critical situations. For example, workload management systems consider that specific messages for the driver are suppressed in certain difficult driving situations until the driving situation is resolved [13]. In collision alert situations, the alert could be initiated with different warn timings, depending on the driver's attention [14].

The focus of adaptivity in the entertainment and information context in the car has mainly been on including the user history in adaptive systems, using their preferences, such as music or navigation [15].

We introduced the Levels of Adaptive Sensitive Responses (LASR) in order to describe the realization of adaptivity in the system [6]. The levels describe the extent to which a system adapts to the user, utilizing a new taxonomy for user-adaptive software in the vehicle. Extending previous taxonomies, LASR is specific about the underlying assumptions concerning groups or individual users and their history. The LASR approach focusses on the understanding

TABLE I
THE LEVELS OF ADAPTIVE SENSITIVE RESPONSES (LASR)

LASR	Caption	Description
LASR 0	No adaptation	Selection by the user is needed every time
LASR 1	Saved	Saved adaptation based on the user selection
LASR 2	Defined	System behaviour reacts according to predefined rules
LASR 3	Learned	System behaviour adapts according to rules live learned in the vehicle
LASR 4	Interpreted	System interprets to inner states, e.g. user emotions, and adapts

of the "nature" of the system, its complexity, dynamics and behaviour.

The LASR framework describes five levels (Table I). The following explanation of the levels includes a comprehensible example use case, showing applicability in the vehicle: The selection of a playlist in the entertainment system.

LASR 0 has no adaptivity. Functions in the vehicle must be selected by the users every time they want to use them. For example, if the user wants to listen to his favourite playlist, he has to manually select the playlist in the infotainment system.

LASR 1 describes how the system can save the individual selections made by a user. The system then requires a certain method for identification. For our playlist example, this implies that once the user selects his playlist as a favourite, the system starts playing the music as soon as the user is identified. The number of functions relating to the specific user is fixed and has been predefined by the developers in advance.

LASR 2 describes how the system contains deterministically predefined rules for adaptivity, i.e. specific if-then conditions. For example, relaxing music starts whenever the car is stuck in a traffic jam on the motorway. This if-then condition is predefined and implemented in all vehicles. The background is knowledge gained in the development phase, where for example user research has shown that most drivers prefer relaxing music when driving in a traffic jam.

With LASR 3, we take a step towards "live" learning, i.e. the system learns about individual actions and reactions in specific contexts. For example, the system learns that the specific user activates the playlist every day when driving home from work (i.e. on a specific route at a specific time). Consequently, the system proposes the activation or activates the playlist anytime the driver is in the same time and place. The major difference to LASR 2 is that this knowledge is learned about the individual user during usage rather than based on assumptions from previously observed behaviour in a group of users.

Finally, LASR 4 includes learning about internal user states. The system is able to make connections between system behaviour, context and user reactions and interprets from that about mood, emotional state or personality. Referring to Peter and Beale [16], "an ideal model of the human user […] includes models of emotion and personality." The user's personality is crucial to understand user experience, attitudes and behaviour [9]. Hence, LASR 4 describes systems that are able to include human states and traits that cannot be observed directly, but need to be interpreted within the adaptive system. For the playlist example this could be that the system suggests the favourite playlist when it detects that the user is stressed or in negative emotional state.

The levels are not mutually exclusive but build upon each other (e.g. a LASR 4 system could include deterministic rules for output or could allow for personalization). Our intention with the LASR was to be able to distinguish and discuss the different system behaviours with a consistent understanding through this taxonomy. We propose to classify a single system on the basis of the highest LASR it is capable of.

III. UX GUIDELINES FOR ADAPTIVE SYSTEMS

Until now, we have described the point of view of system design by focusing on the input parameters. However, the mental modal that a user has about a system is mediated by the HMI design and the users' perceptions might not represent the actual level of automation or LASR. In general, increasing the complexity of systems leads to decreasing predictability and linearity [17]. "One needs to gain a fundamental understanding of the emergent properties that result from the intricate interactions of the complex system's components, including the humans in those systems" [18].

Addressing the factors that influenced the use of automation, Parasuraman *et al.* [19] distinguished between adaptive aiding and adaptive task allocation as two different approaches for adaptive automation. Adaptive aiding includes the context specific presentation of necessary information to the user. Adaptive automation describes task allocation from the user to the system or vice versa.

As standard recommendations, UX designers orientate on the design principles for interactive systems defined in ISO norms [20]. Adaptive systems in terms of the LASR definition challenge these traditional design guidelines for non-adaptive systems. For example, the design principle consistency could contradict context-adaptive system states.

Based on previous research cited in the following paragraphs, we propose considering the following five UX design principles for adaptive systems. While *intuitive design* is based mainly on the standard definitions for user friendly system design, transparency, proactivity, intelligence and empathy foremost address on creating the specific use perception of the adaptive system.

A. Intuitive Design

Similar to non-adaptive systems, the HMI of adaptive systems should be designed for intuitive usage. A technical system is, in the context of a certain task, intuitively usable while the particular user is able to interact effectively, not-consciously using previous knowledge [21]. According to the ISO Standard, the HMI is suitable for the task, supporting the user in the completion of the task, regardless of the technology, or conformity with user expectations [20] It is expected that the likelihood for making usage errors and the number of steps needed to fulfil a task will decrease with increasing adaptivity, because the adaptive system anticipates the user's input in advance.

Hence, we state that an intuitive design of an adaptive system may not require prior knowledge for use.

B. Transparency

As described above, classic automation nomenclatures describe how transparent the system is about options and the choices it makes [9]. The ISO 9241 dialogue principle self-descriptiveness contributes to perceived transparency. Self-descriptiveness in its original definition includes that "at any time it is obvious to the users which dialogue they are in, where they are within the dialogue, which actions can be taken and how they can be performed" [20]. Walter [2] emphasized that transparency (along with proactivity) is a crucial parameter for user acceptance of adaptive systems. In their evaluation of an in-car recommendation system, Bader *et al.* [22] showed that user decision-making in interaction with a system that is highly adaptive in terms of limited information presentation was supported by high transparency of the system. Higher transparency should also include that users are aware of the system limitations as well as the current state of the system.

In line with this, Eiband, Völkel, Buschek, Cook, and Hussmann [23] concluded that users have a desire for explanation on how the system works and sometimes even want to try it out "live", e.g. changing settings and seeing the resulting differences in the system and the algorithm output. Transparency also includes the user understanding which (personal) input data is used at any touchpoint with the system. Contributing to a correct mental model of the system, the user should be aware of which system sensors are active and which data is interpreted from that. For example, the drowsiness detection in a car operating on LASR 4 could use driving data (steering behaviour), context data (duration of the trip) or physiological data (measured by camera or other physiological sensors). A highly transparent adaptive system makes this information available to the user.

Amershi *et al.* [24] cover transparency by their Guidelines G1 ("Make clear what the system can do"), G2 ("Make clear how well the system can do what it can do"), G11 ("Make clear why the system did what it did"), G16 ("Convey the consequences of user actions") and G18 ("Notify users about changes").

For the current setup, we realized transparency by providing context information along with the information that either the system has learned about the preferences of the individual user or follows deterministic rules.

To sum up, the perceived transparency describes that the user is able to understand the background for the system actions and reactions [25].

C. Proactivity

The golden rule "enable frequent users to use shortcuts" by Shneiderman *et al.* [26] explains that "as the frequency of use increases, so do the user's desires to reduce the number of interactions and to increase the pace of interaction. Abbreviations, function keys, hidden commands, and macro facilities are very helpful to an expert user." Proactivity is defined by how independently the system handles adaptation and relating to that how many interaction steps the user has to perform himself [27]. If the system asks the user for user confirmation every time before making an adaptation, the perceived level of proactivity is low. Low levels of proactivity could be recommended for extensive system changes that influence many other features or future interactions. With that, the level of proactivity relates partly to the level of automation by Parasuraman *et al.* [9]. Walter [2] showed that higher levels of proactivity in an in-vehicle recommender systems lead to a significant reduction of driver distraction. Eiband *et al.* [23] stated that while users appreciate system suggestions, they still want to remain in control. With that they recommend the realisation of a level of system proactivity or of user control that allows the user to make good decisions themselves and that provide options for controlling the algorithm output. There should also be a facility for turning the adaptivity of the system on or off.

In sum, proactivity is realized by the number of necessary interactions that the user needs to undertake to achieve her/his goals.

D. Intelligence

We believe that intelligence is another essential descriptor for adaptive systems in the vehicle. For example, detecting individual driver fatigue requires LASR 4 technology, but simply presenting the user a coffee cup in the HMI with the note to make a break does not appear to be very smart. Making a situationally aware recommendation of how the user can cope with the detected drowsiness instead would make the system appear intelligent. In the field of AI, Wahlster and Maybury [27] defined intelligent user interfaces as "human-machine interfaces that aim to improve the efficiency, effectiveness, and naturalness of human-machine interaction by representing, reasoning, and acting on models of the user, domain, task, discourse, and media (e.g. graphics, natural language, gesture)." To describe the term intelligence from a user experience perspective Völkel *et al.* [7] ran a text analysis to extract all occurrences of "intelligent" in all IUI proceedings and found that "adaptation, automation, and interaction are the most common aspects that IUI researchers highlight when describing something as intelligent." Following Whalster and Maybury [27] who postulate that the "models of the user" are important, we define intelligence represented in the HMI as the ability to make it obvious to the user that the system understands situational and personal contexts and discovers logical correlations. We believe that the advanced technology that defines higher LASR is independent of the level of intelligence that the system represents in the HMI. Even a low LASR within the framework can appear intelligent in the user's eye if the adaptation is done with "common sense" so that the adaptations are compliant with the user's expectations. For example, a system might detect that the outside temperature is under the defined threshold and therefore increases the temperature of the seat heating (LASR 2). When presented appropriately through the HMI, the user will probably understand the adaptation as reasonable and evaluate the system as intelligent.

In summary, a user experiences a system as intelligent when the system decisions and actions appear reasonable and meaningful in the current situation.

E. Empathy

High perceived empathy is achieved when the user has the impression that the system understands his individual needs, desires and goals. So, while an intelligent system acts reasonable and based on the consideration of different (situation aware) parameters, a system is perceived as empathetic when the user notices that his/her individual preferences are considered. Heimgärtner *et al.* [28] stated that empathy is a key factor in HMI design. For example, high perceived empathy can be achieved by ensuring that the user's privacy is protected by hiding sensitive information when other users who are not closely related are also in the car. Another example is that the system does not point out the temporary deficit in the user's driving skills due to fatigue in the presence of other occupants. A possible adaptation could be the activation of higher levels of assistance, which could happen without even telling the user. Studies have shown that in the context of driver assistance systems, this strategy prevents negative behavioural adaptation [14]. In a more advanced system, information with emotional content could be held back for appropriate moments in which the user is relaxed, happy or in any other appropriate state. A system with high empathy also takes into account the user's cognitive abilities, e.g. short-term memory [26] or the individual usage history, e.g. familiarity with the system. Again, it is important to understand that systems with all levels in the LASR framework can cause high levels of perceived empathy in the user, depending on the staging in the HMI. Along with Eiband *et al.* [23] we believe that a system that appears empathic also appreciates suggestions, corrections and feedback by the user.

With the goal of making systems more and more empathic, steps towards the digital assistants representing the system HMI are taken [29]. In line with that, Völkel *et al.* [30] developed a personality model of digital conversational agents. They assumed that the personality of the digital agent communicating systems functions might influence how empathic the overall system might appear.

Hence, a user experiences a system as empathetic when his/her individual preferences and needs are considered in the algorithm.

To sum up, we propose that the HMI aims to present the system in an intuitive, transparent, proactive, intelligent and empathic way and with that triggers the according perceptions in the user. We thereby assume that there is an interaction between system design and HMI design and that different HMI aspects are more or less important for different levels of adaptivity. Furthermore, our HMI guidelines are still rather broad and so far only based on the cited literature. There may be several sub-constructs for each of the guidelines. Nevertheless, we believe that these provide enough clarity for an initial quick and rough evaluation of the correlation between system and HMI design for adaptive systems.

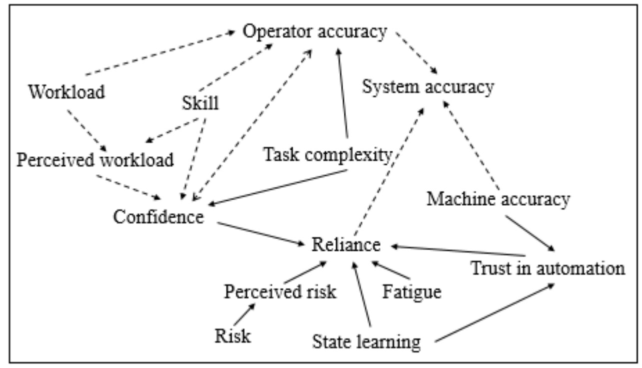

Fig. 4. Describing interactions of factors influencing automation use. Solid arrows: based on experimental data. Dotted arrows: hypotheses; from Parasuraman and Riley [8].

Additionally, within the process of system design, it is also necessary to evaluate whether the system is perceived in the intended way and in turn, also leads to high likability of the system. For example, Weitz and colleagues investigated a virtual agent in order to support transparency and comprehensibility of AI-based interaction design [31]. The participants evaluated the different versions of the AI agent based on the dimensions helpful, comprehensible, trustworthy and likable, and according to whether participants would want to interact again. Parasuraman and Riley [8] described the effects of automation misuse, disuse or abuse caused by incorrect mental models or challenging user states. Amongst others, perceived workload, trust in the system, or the perceived risk contribute to this (Fig. 4), which emphasizes the importance of differentiating HMI design and the user perception.

In the following section we present a study evaluating the relationship between in-vehicle systems with different LASR and HMI design and the user's perception of the system, whereby user perception is measured according to the above described HMI design dimensions.

IV. Empirical Investigation

In an online survey, we investigated the influence of LASR and system transparency on the user's system perception in two different scenarios relevant in the vehicle. The goal was to investigate whether systems with different LASR lead to changes in the user's perception of the system and in particular, whether the postulated UX guidelines intuitive design, transparency, proactivity, intelligence and empathy are meaningful measures for the user's perception of the adaptive system. We focused on the difference between LASR 2 and LASR 3, because here one of the core aspects of the levels is varied: adaptive behaviour due to deterministic rules vs. adaptive behaviour based on learning individual behaviour. Furthermore, the study aimed at providing some insight into the potential interaction between LASR and the UX guidelines. To keep the study design and the number of system versions reasonable, we followed up previous research and focused on the factor transparency.

A. Participants

50 participants (28 female, 22 male) took part in the online survey. They assigned their age to one of six groups, resulting in the following distribution: n = 0 for age <20 years, n = 7 for age 20-29 years, n = 21 for age 30-39 years, n = 9 for age 40-49 years, n = 7 for age 50-59 years and n = 6 for age >60.

B. Study Design

The independent variables were LASR (2 vs. 3), the realized transparency of system adaptations (with vs. without) and the scenario (navigation vs. climate control). The conditions were realized through descriptive texts and within fictitious graphical user interfaces (GUI) containing the relevant variations in information. As dependent variables, we measured the perceived intuitive design, transparency, proactivity, intelligence and empathy in terms of subjective answers in a questionnaire. Moreover, participants gave open explanations on their system understanding and we asked for an overall ranking of the system versions according to preferences. The study had a full within-subjects design; hence all participants experienced all experimental conditions. The order of presentation was permuted between participants.

Our hypotheses were:

- The system versions with transparency lead to higher perception of transparency in the participants compared to the versions without transparency.
- The system versions with LASR 3 lead to higher perceived intelligence and empathy compared to the system versions with LASR 2.
- There is an interaction between LASR and transparency variation showing that with transparency the LASR 3 system versions are perceived as more intelligent than the LASR 2 while no difference in intelligence is experienced without transparency.
- There is no difference in system perception between the use cases (navigation vs. climate control).

C. Scenarios

Two different car-relevant use cases relating to two different systems in the vehicle were investigated: navigation and climate control. Each scenario started with an instruction on the background situation.

For the navigation scenario, participants were instructed to select one of three different use cases based on their daily routine. They selected either dropping off their partner at work in the morning, bringing their kids to kindergarten/school in the morning or passing by the post office after work in the afternoon. We introduced this differentiation in order to address an adaptivity in the navigation function that every participant could relate to. 24 participants selected the kindergarten scenario; 6 stated they relate to dropping off their partner in the morning; 20 participants selected frequently stopping by the post office. The scenario selection had no influence on the realization of the factors LASR and transparency, but only ensured that every participant could relate to the system description.

TABLE II
DESCRIPTION OF SCENARIOS REALIZED IN THE INTERFACE SCREENS

Condition	Navigation	Climate Control
LASR 2 – no transparency	User stores specific navigation destinations as favourites. System activates destinations without explanation.	System activates climate control features without explanation.
LASR 2 – transparency	User stores specific destinations as favourites. System informs that destinations are activated due to time of day (e.g. going to work happens in the morning).	System activates climate control features and explains that the features are activated due to outside weather conditions.
LASR 3 – no transparency	System recognizes destination sequence from previous trips, i.e. system recognises which destination the user is going to in which sequence and at which time of day. System sets target destinations without explanation.	System recognises climate control settings from previous usage of the user in the same context. System changes climate settings without explanation.
LASR 3 – transparency	System recognises the destination sequence from previous trips, i.e. system recognises which destinations the user is going to in which sequence and at which time of day. System sets target destinations with explanation that previous trip data are considered	System recognises climate control settings from previous usage of the user in the same context. System changes climate settings with explanation about considered data from previous trips.

Within the scenario, the navigation system proposed navigation either as a predefined route to a fixed, saved destination (LASR 2) or according to a route identified in everyday usage (LASR 3) based on the individual selection. For the climate control scenario, the climate system adapted either to fixed values related to the outside weather conditions (LASR 2) or based on the learned user behaviour in the specific situation (LASR 3).

Table II provides an overview of the variations in the system according to the different study conditions.

D. Materials and Procedure

The study was realized as an online survey targeting German subjects. After filling in demographic data, the participants were given the explanation that the study was about the evaluation of different in-vehicle GUI screens. They then selected one of two personalization icons (penguin vs. dog) accompanied by the instruction that any time there was a feature active that considered their individual user history (LASR 3), this icon would appear on the screen (Fig. 5).

Each screen, i.e. every scenario and experimental condition, was introduced with a short explanatory text followed by the

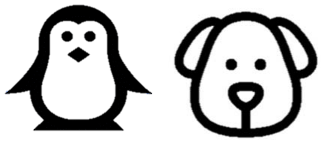

Fig. 5. Personalization icons used in the screen for LASR 3 system versions.

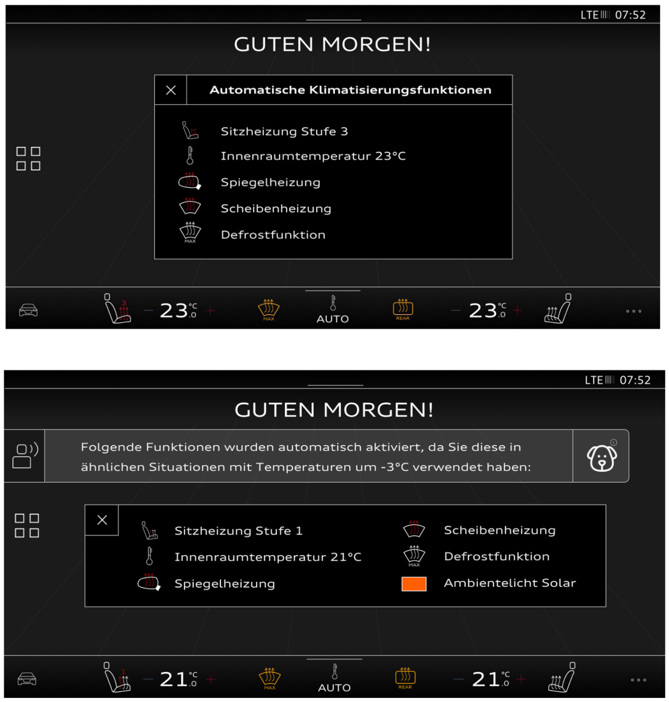

Fig. 6. Example screens for the use case climate control. The upper picture shows LASR 2 with no transparency; the lower picture shows LASR 3 with transparency. The text in the explanation window to the left of the dog icon says "The following settings were activated automatically because you have used it this way in similar conditions at −3°C in the past."

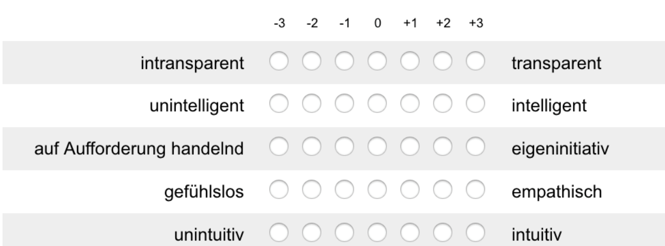

Fig. 7. Participants were asked to rate each system version according to the 5 items in German: "Not transparent/transparent", "Not intelligent/intelligent", "Acting only on demand/proactive", "Insensitive/empathic", and "Not intuitive/intuitive."

relevant in-vehicle GUI screen. Fig. 6 shows two example screens.

The scenarios in each condition were then evaluated by the participants according to the five HMI design guidelines described above, using a 7-point scale from −3 to +3 (Fig. 7). We used this short questionnaire for the online study in order to keep the processing time for each participant reasonable.

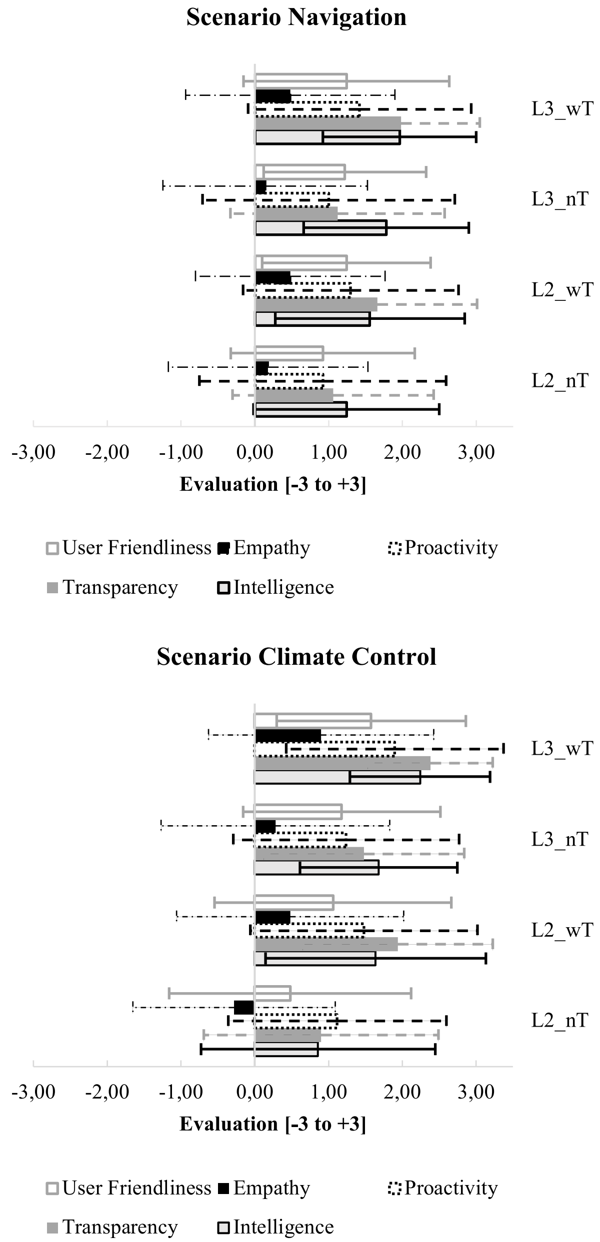

Fig. 8. Means and + standard deviations for the perception of the five HMI design guidelines differentiated for the conditions LASR (LASR 2 = L2 vs. LASR 3 = L3) and transparency (no transparency = nT, with transparency = wT) [n = 50].

Following the evaluation of each version according to the five items, participants were asked about their understanding of how the system works with an open question. They entered their open answers to the question "Why do you think the system is showing that screen?" After experiencing all conditions, participants were asked to rank the HMI versions varying LASR and transparency in the climate control screen according to their favourite (rank 1), second favourite (rank 2), third favourite (rank 3) and least favourite (rank 4) version.

E. Results

Investigating the influence of the factors LASR, transparency and scenario, we averaged the questionnaire answers for the five HMI design guidelines given after the presentation

TABLE III
ANOVA RESULTS FOR THE FIVE DEPENDENT VARIABLES

Effect	Perc. intuitive design	Perc. trans-parency	Perc. pro-activity	Perc. intelli-gence	Perc. empathy
Scena-rio (S)	F(1.49)= 0.383; *p*=0.539	F(1.49)= 3.025; *p*=0.088	F(1.49)= 3.112; *p*=0.084	F(1.49)= 0.072; *p*=0.790	F(1.49)= 0.08; *p*=0.779
LASR (L)	**F(1.49)= 13.335; *p*=0.001**	**F(1.49)= 14.64; *p*<0.000**	F(1.49)= 2.339; *p*=0.133	**F(1.49)= 28.696; *p*<0.000**	F(1.49)= 4.521; *p*=0.039
Trans-paren-cy (T)	**F(1.49)= 8.455; *p*=0.005**	**F(1.49)= 27.767; *p*<0.000**	**F(1.49)= 10.743; *p*=0.002**	**F(1.49)= 9.376; *p*=0.004**	**F(1.49)= 10.035; *p*<0.000**
S x L	F(1.49)= 4.133; *p*=0.047	F(1.49)= 2.56; *p*=0.175	F(1.49)= 0.601; *p*=0.442	F(1.49)= 1.253; *p*=0.268	F(1.49)= 6.656; *p*=0.013
S x T	F(1.49)= 3.59; *p*=0.064	F(1.49)= 1.818; *p*=0.184	F(1.49)= 0.23; *p*=0.633	**F(1.49)= 7.242; *p*=0.010**	F(1.49)= 6.858; *p*=0.012
L x T	F(1.49)= 1.761; *p*=0.191	F(1.49)= 0.157; *p*=0.694	F(1.49)= 1.341; *p*=0.252	F(1.49)= 1.658; *p*=0.204	F(1.49)= 0.147; *p*=0.703
S x L x T	F(1.49)= 0.134; *p*=0.716	F(1.49)= 1.704; *p*=0.198	F(1.49)= 0.572; *p*=0.453	F(1.49)= 0.097; *p*=0.757	F(1.49)= 0.438; *p*=0.511

Bold numbers indicate significant effects with an alpha level of .01. Perc. = Perceived.

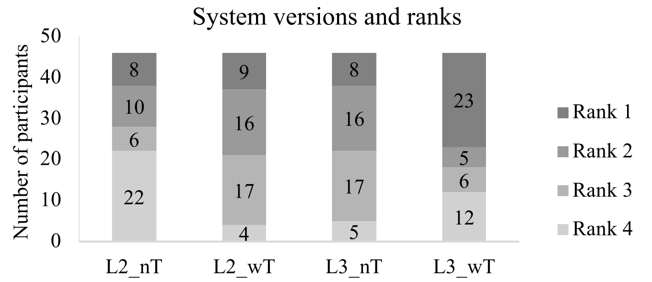

Fig. 9. Number of participants ranking certain system versions on rank 1, 2, 3, and 4 [n = 46]. LASR (LASR 2 = L2 vs. LASR 3 = L3), transparency (no transparency = nT, with transparency = wT).

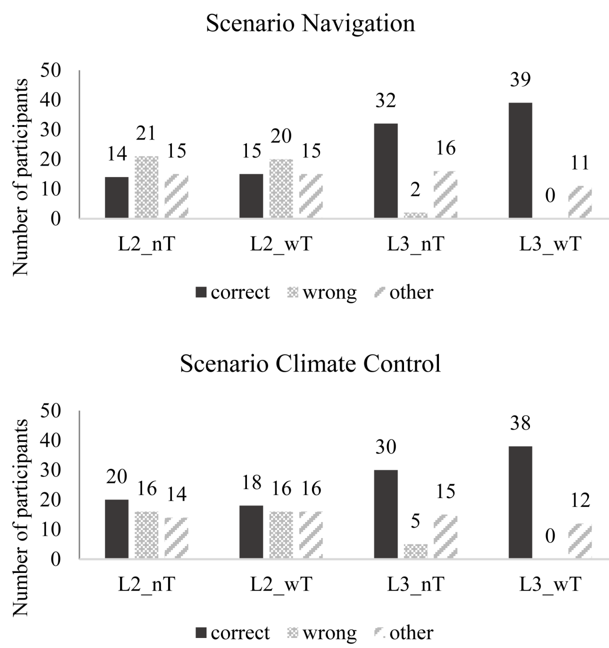

Fig. 10. Number of participants understanding the functioning of the system correctly or incorrectly for the two scenarios navigation (upper graph) and climate control (lower graph). The category "other" describes participants' answers not relating to the functioning of the algorithm. LASR (LASR 2 = L2 vs. LASR 3 = L3), Transparency (no transparency = nT, with transparency = wT).

of each of the system versions. Fig. 8 depicts means and standard deviations of the perception of the HMI design guidelines separated by LASR, transparency and scenario. In general, the results show that higher LASR and more transparency lead to higher evaluation along the perception of the five HMI design guidelines. Empathy is the dimension with the lowest average values.

For each dependent variable, a $2 \times 2 \times 2$ within-subjects ANOVA was conducted with the factors scenario (navigation vs. climate control), LASR (LASR 2 vs. LASR 3) and system transparency (no transparency vs. with transparency).

Table III shows the ANOVA results for the dependent variables perceived intuitive design, transparency, proactivity, intelligence and empathy. The alpha level for significant results was Bonferroni adjusted to .01. The results show that the scenario had no significant effect on system perception. The LASR level influenced the users' perception of intuitive design, transparency and intelligence, with higher values given to the LASR 3 system. Varying transparency influenced all dependent measures. Higher transparency as operated in the study lead to higher perceived intuitive design, transparency, proactivity, intelligence, proactivity and empathy.

After experiencing all system versions, participants ranked the versions according to their preferences. Four participants were excluded from this analysis because they did not fill out the online form as instructed (naming two versions on the same rank). Fig. 9 shows that the system version with LASR 3 and transparency was rated as the favourite by the largest group of participants [n = 23]. However, the second most frequent ranking for L3_wT is rank 4.

Finally, we investigated the answers the participants gave on their understanding of how the system works after experiencing each of the versions. Fig. 10 shows the proportion of participants giving answers categorized as correct and categorized as incorrect. All answers that did not relate to the system itself or the algorithm behind it (e.g. relating to the GUI design) were categorized as "other".

The number of participants with an incorrect understanding of the system background was larger in the LASR 2 condition than in the LASR 3 condition. Higher transparency did not significantly increase the number of participants with a correct understanding. Analysis of the answers showed that 100% of the participants with an incorrect understanding of the LASR 2 system gave explanations matching the LASR 3 system. Thus, they believed they were interacting with a LASR 3 system even though the scenario and the screens were instructed as LASR 2.

Following this, we extracted only answers to the questionnaires evaluating the systems based on a correct and incorrect

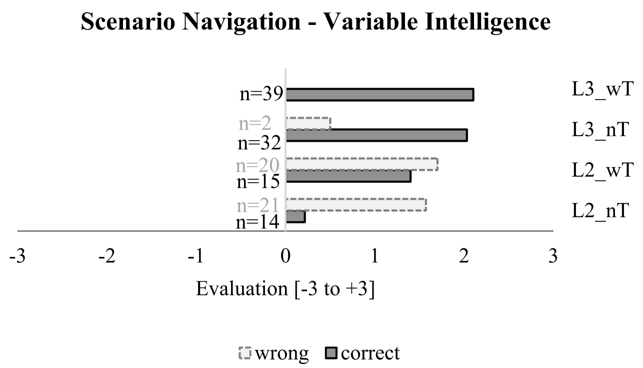

Fig. 11. Example of the evaluation of intelligence in the scenario navigation differentiated for participants who correctly understood how LASR 2 and LASR 3 work and for those who had an incorrect understanding of how they work. Note that for the L3_wT condition no participant had an incorrect understanding of the algorithm. LASR (LASR 2 = L2 vs. LASR 3 = L3), transparency (no transparency = nT, with transparency = wT).

classification. Fig. 11 shows an example result for the scenario navigation and the variable intelligence. As expected, the mean intelligence perceived by participants believing that they experienced a LASR 3 system was higher than the mean intelligence perceived by participants who understood the difference between LASR 2 and LASR 3.

The effect of LASR on the perceived intelligence discussed in Fig. 8 is therefore expected to be much stronger than we could actually show. Due to the uneven sample sizes, no further statistics were calculated for this part of the analysis.

V. Discussion

We presented different classifications for intelligent systems including the Levels of Adaptive Sensitive Responses (LASR) as a new taxonomy for adaptive systems in the vehicle. Additionally, we introduced a discussion on the user-centred design for adaptive in-vehicle systems, focusing on the five main aspects: perceived intuitive design, transparency, proactivity, intelligence and empathy.

In an online study we showed that the perceived intelligence, transparency and intuitive design differ between systems with either LASR 2 or LASR 3. Hence, the LASR classification is not only relevant for defining the necessary technical input of a system, but is also relevant in terms of how the user perceives the system.

Our variation of system transparency influenced user perception for all five HMI design aspects. This shows that not only the level of adaptivity in the system but also the presentation of the system in terms of transparent communication influences how intuitive, transparent, proactive, intelligent and empathic the system is perceived to be. This is interesting as it points towards relationships between the HMI design guidelines. The realization of transparency in our setting made the system appear more empathic and intelligent, maybe just because the system intelligence was more obvious in these versions. Higher perceived proactivity could be attributed to a system communicating the system background (as was the case in our study), or could also be attributed to a system adapting functions without explaining the reasons. More research is necessary to clarify the connection between the HMI guidelines and system perception. Furthermore, transparency in terms of explanations on system behaviour needs to be evaluated in the context of driver distraction and (visual) information overload in a natural driving setting.

In our study, the scenario did not have a significant main effect on the system perception in terms of the five HMI design guidelines. If that assumption holds true, it would be possible to deduce general UX guidelines with known effects in the vehicle. However, some significant or almost significant interactions between scenario and transparency design point towards the assumption, that the perception of system intelligence is also influenced by the function and the context itself. Hence, future research should investigate if depending on the context, the design on the system is perceived differently.

Even though most of the participants preferred LASR 3 with transparency as their favourite system version, there was still a significant number of participants who favoured LASR 2 systems or disliked LASR 3 systems. Individual preferences on data usage and adaptivity could therefore be considered in future adaptive systems.

The results have to be interpreted by considering system understanding, i.e. if and how users had the right mental model. We showed that a significant proportion of participants did not understand the LASR 2 version correctly, but interpreted the functionality as LASR 3. Consequently, they evaluated the LASR 2 system believing the system was LASR 3 and with that assumed that the system was more intelligent than it actually was. That makes clear that a high user experience and the perception of high technical sophistication do not always require the highest LASR. Instead, a low LASR with no learning components but in terms of HMI guidelines, well-designed system with the adaptation applied in the right context might be experienced as highly intelligent.

As this was true for systems with and without transparency, we conclude that communicating the system behaviour transparently did not lead to higher numbers of users obtaining the right understanding in our setting. One approach could be to improve the system explanations in the transparency conditions, i.e. improving the operationalization of transparency. Another explanation might be that switching between mental models of the LASR 2 and LASR 3 system in our within-subjects study design was challenging for some participants. It might be that perceiving a system with a certain level of intelligence influences the expectations on another system in the same vehicle and that in particular switching back to a system with lower intelligence is challenging for users. Nevertheless, the results are encouraging in terms of the influence of LASR on system perception. We showed that the differences between LASR 2 and LASR 3 in the five dependent measures were even larger in participants who had the right mental model and that LASR is a relevant influence on the user's perception of the system. On that account, we conclude that describing the adaptive system in terms of intuitive design, transparency, proactivity, intelligence and empathy seems to be a promising approach.

Future studies will address the correlation between other LASR levels and the remaining HMI guidelines. The hypotheses will thereby be investigated if the highest and lowest LASR lead to higher and lower empathy and intelligence perception and how the presentation of the system influences that. Along with that, it is necessary to investigate the operationalization of the five HMI design guidelines intuitive design, transparency, proactivity, intelligence and empathy, both in terms of realization in the HMI and in terms of measuring the perception in the users. For the former, we need to define the most appropriate ways for the HMI design guidelines which lack sufficient literature to date (e.g. realizing empathy). For the latter, it might be beneficial to use more detailed scales and questionnaires to elaborate on each of the UX design guidelines. With the online questionnaire setting we aimed for a simple evaluation of the perception of the five constructs with one item for each dimension. As mentioned above, each of the dimensions relates to different sub-constructs and it might be beneficial to elaborate on in more detail via questionnaires. The correlations between the constructs are of particular interest. For example, high levels of transparency realized by frequent declarations on data use might interfere with high levels of perceived intuitive design. Also, a validation of the questionnaire is on our future research agenda.

Moreover, our study focused on a one-time evaluation of system states, which influences the validity of evaluating an adaptive system. For example, it is comprehensible that some of the participants mentioned that they liked the transparent explanation of the system, but that they could dispense with those in repeated usage. Hence, studying the design and user perceptions in longitudinal studies would provide important insight into system adaptations with regard to repeated exposure and increasing experience.

An important factor is that the LASR framework does not include a classification of system quality so far. For example, Völkel *et al.* [32] showed that users are able to manipulate their personality assessment established by an automatic chatbot. Cramer *et al.* [33] showed that inaccurate empathic responses of a system lead to decreasing trust in the system. Hence, on each LASR it is important, to set targets and thresholds for algorithm reliability. This is still challenged by the difficulties of adaptive systems in terms of the correct identification of user states such as emotions or moods [4]. Valid human state detection needs unobtrusive physiological and neurological measurements and a better understanding of the translation of user state and the current situation into adaptive system functions. Many of the (in the vehicle affordable) sensors have not yet reached a reliable signal quality, especially considering some of the challenging conditions in the vehicle (e.g. vibrations, temperature, lightning). In case of the incorrect interpretation of a situation or user state, systems might end up with bothering users or, in the worst case, with creating safety-critical situations. Current studies indicate that technological progress has not yet overcome many challenges for correct state detection [34].

When evaluating user adaptive systems, it is inevitable to discuss data protection and paternalism. In particular, with modern data protection laws and users who are highly sensitive about their data and its usage, adaptive systems need to satisfy high data protection standards. In terms of user experience, it might be that the described taxonomy of how users perceive adaptive systems relates to attractive qualities as described in the KANO model [35], while aspects like data protection and avoidance of paternalism are must-be qualities. As a deduction, the general acceptance of adaptive systems depends on clear safety standards and their transparency for the user.

Finally, we believe that a major benefit of the LASR framework is to support managing expectations in the ever faster growing area of AI and user state identification. Sensor technologies and algorithms that are more intelligent bring value to the user within meaningful contexts and when presented according to HMI guidelines based on human factors. In that sense, the LASR concept requires further evaluation in terms of its applicability and usability for developers and researchers in order to evaluate whether it can be a significant tool for describing the technical realization of features.

VI. Conclusion

We have discussed the classification of adaptive systems and presented the Levels of Adaptive Sensitive Responses (LASR) as a classification of the intelligence of interactive systems in the vehicle. Additionally, we have introduced five design dimensions guiding the development of HMI concepts of adaptive systems, with the expectation that those shape the user experience. Our study shows that both LASR and the HMI design influence how the adaptive system is perceived. However, a significant proportion of users built the wrong mental model for the presented systems. More research is necessary to elaborate on the overall usefulness and usability of the LASR framework, to detail the HMI design recommendations and to evaluate the user experience depending on system and HMI design.

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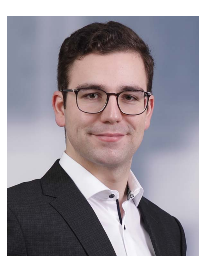

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