Effect of Visualization of Pedestrian Intention Recognition on Trust and Cognitive Load

Mark Colley
mark.colley@uni-ulm.de
Institute of Media Informatics, Ulm University
Ulm, Germany

Christian Bräuner
christian.bräuner@uni-ulm.de
Institute of Media Informatics, Ulm University
Ulm, Germany

Mirjam Lanzer
mirjam.lanzer@uni-ulm.de
Institute of Psychology and Education, Dept. Human Factors, Ulm University
Ulm, Germany

Marcel Walch
marcel.walch@uni-ulm.de
Institute of Media Informatics, Ulm University
Ulm, Germany

Martin Baumann
martin.baumann@uni-ulm.de
Institute of Psychology and Education, Dept. Human Factors, Ulm University
Ulm, Germany

Enrico Rukzio
enrico.rukzio@uni-ulm.de
Institute of Media Informatics, Ulm University
Ulm, Germany

ABSTRACT

Autonomous vehicles carry the potential to greatly improve mobility and safety in traffic. However, this technology has to be accepted and of value for the intended users. One challenge on this way is the detection and recognition of pedestrians and their intentions. While there are technological solutions to this problem, there seems to be no research on how to make this information transparent to the user in order to calibrate the user's trust. Our work presents a comparative study of 5 visualization techniques with Augmented Reality or tablet-based visualization technology and two or three information clarity states of pedestrian intention in the context of highly automated driving. We investigated these in a user study in Virtual Reality (*N*=15). We found that such a visualization was rated reasonable, necessary, and that especially the Augmented Reality-based version with three clarity states was preferred.

CCS CONCEPTS

• **Human-centered computing → Human computer interaction (HCI)**; *Haptic devices*; User studies.

KEYWORDS

Autonomous vehicles; pedestrian intention; interface design.

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1 INTRODUCTION

Autonomous vehicles (AVs) are expected to change the interaction between driver and vehicle profoundly [10]. However, public opinion on AVs can be described as skeptical: Kyriakidis et al. found that 65% of the participants were worried about the reliability of automated cars [31]. Continental AG found in a survey conducted in seven countries that between 43 and 74% of the participants doubted that automated cars will function reliably (Chinese being the most pessimistic with 74%) [1]. In their assessment of the Pedestrian Detection System, respondents were asked "Spontaneously, how would you classify this system, which automatically brakes your car if a pedestrian or cyclist unexpectedly and suddenly steps in front of you on the road?" While convenience received a good rating ($M \approx 2$; *1 = convenient* to *5 = inconvenient*), technical maturity assessment was lower (e.g., Germany: $M \approx 3.1$; *1 = technically mature - 5 = Not technically mature*). Lack of trust in the automated features could lead to decreased willingness to use these. Visualizing the deducted intentions of other road users, especially very mobile pedestrians, could increase trust and also enable better assessment of technical maturity, providing system transparency.

Pedestrian intention recognition until now was investigated mainly from a technological standpoint [3, 7, 48, 52]. Therefore, we propose to include visualizations of pedestrian intention recognition to calibrate trust for passengers of AVs and, therefore, to increase usage [19]. High pedestrian-related accidents ($\approx$ 21% of all road accidents in the EU in 2016 [11]) indicate that the recognition of the intention is even difficult for humans. While traffic-related objects such as other obfuscated cars were highlighted [65], pedestrian intention visualization as an especially relevant factor influencing the trajectory of the AVs was not yet evaluated.

The main contributions of this work are: (1) Unveiling the lack of visualization techniques for pedestrian intention visualization and its consequences on trust and cognitive load. (2) Proposal of technology-dependent visualization techniques. (3) Findings of a Virtual Reality (VR) study (*N*=15) show that an Augmented Reality (AR) visualization helps to reduce cognitive load and that all visualization concepts as well as the presentation of more information positively affect trust. In this context, clarity states refers to the granularity (higher equals more information content) of which pedestrian intention is shown. In general, participants claimed that the visualization of the recognition of pedestrians and their intention is reasonable and necessary.

2 RELATED WORK

This section presents an overview of trust and system transparency. Additionally, we show visualization techniques both in academia and industry in the automotive field with a focus on pedestrian intention recognition.

2.1 Trust and System Transparency

Trust in an automated system plays an essential role in the decision to use it. Distrust can lead to an overly skeptical behavior towards automated systems which makes them prone to be used less [38], missing out on the beneficial effects of these systems [44]. Overtrust, on the other hand, can lead to fatal consequences [41]. Therefore, the aim should be *calibrated trust* [38] where the user's trust reflects the actual capabilities of the automated system. To develop calibrated trust, distrust must be overcome and overtrust must be prevented. This can be accomplished before, during, or after interacting with an automated system [20]. Providing relevant information such as system transparency or system reliability helps to build and maintain trust in automated systems [12, 18, 26, 30]. Forster et al. [12] showed that participants who observed videos of a driver interacting with a conditionally automated vehicle trusted a system introduced as highly reliable significantly more than a system introduced as little reliable. Kraus et al. [30], who conducted a driving simulator experiment within a highly automated setting, found that a system with low transparency led to a decrease in trust after a malfunction while a highly transparent system prevented this decline in trust.

2.2 Pedestrian Intention Recognition

Rasouli and Tsotsos [46] gave an overview of pedestrian intention recognition techniques. Some models base their estimation solely on dynamic information (e.g., position and velocity [51]) or include information about the scene such as traffic signalling [17]. Brouwer et al. [6] compared different information on pedestrian motion models. The combination of the dynamics of pedestrians, their 3D pose and awareness (meaning head orientation towards the vehicle), and obstacles lead to the best prediction results. Other factors were included as focusing on trajectories and dynamic factors alone is insufficient [48]: awareness [6], social forces [37] (i.e., repulsion and attraction), or structure of the street [49]. Rasouli and Tsotsos [46] summarize: "intention estimation algorithms are used in very limited traffic scenarios [...] Ideally, these algorithms should be universal" [46, p. 915]. While most algorithms use trajectories and scene dynamics, this is unreliable as "Just Motion Is Not Enough" [46, p. 914]. Kong and Fu [24] presented a survey on human action recognition and prediction. Various action prediction methods were compared on 8 datasets. Performance varies greatly both depending on the dataset as well as on the method. The best performance in 2018 with 88.37% was by mem-LSTM [25] on the UCF-101 dataset [54] with an observation ratio of 0.5, meaning that half of the video was shown to the network. With an observation ratio of 0.1, the performance dropped to 51.02%.

2.3 Visualization in Vehicles

In-vehicle visualization is a broad topic including safety critical but also infotainment aspects. Wiegand et al. [63], for example, present a design space that captures possible use cases for AR applications. They categorize these into five clusters: *Safety*, *Navigation*, *Convenience*, *Entertainment & Communication*, and *Vehicle Monitoring*.

Head-Up Displays (HUDs) are researched as an approach to avoid drivers of diverting their attention away from the street. Smith et al. showed that performance measures are better when using this technology compared to traditional Head-Down Displays (HDDs) [53]. Windshield Displays (WSDs) take this one step further by creating an HUD that covers the entire windshield. A view management system for WSDs was already presented [15]. The ultimate goal is to be able to show content at continuous depth [15]. Gabbard et al. [13] highlighted advantages of such systems allowing AR information visualization: no need to look down, spatial proximity, and novel sources of available information. Also, challenges, which are mainly of technical nature but also include visual clutter and driver distraction, were discussed [13].

With AVs becoming reality, calibrating trust and improving situation awareness (SA) could increase acceptance of such novel technology. Various work already included different information visualization of the AV to the passenger.

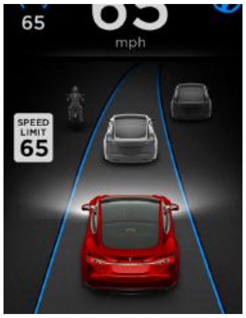
Löcken et al. investigated the usage of ambient light to inform the user of the decisions of their automated vehicle [36]. LED strips between the A- to B-pillars were used to indicate *accelerating*, *braking*, and *changing lanes* [36]. Being *Work-in-Progress*, the systems were rated as intuitive but still had inconsistencies.

Lindemann et al. [35] used an AR WSD to display a variety of information such as destination, regulations, and navigation. They also highlighted threats such as pedestrians and provided a cube over moving vehicles indicating their behavior (e.g., dangerous or unusual). They showed higher SA in low and high visibility scenarios compared to only having the basic elements speed and navigation info.

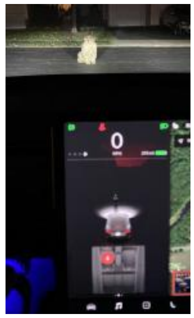
Trust in automated vehicles was researched in various ways. For semi-autonomous vehicles, Koo et al. [26] investigated which type of message regarding the actions ("how" information) and the reasons ("why" information) for these lead to increased trust. Only providing why information led to highest trust. They argue that additionally providing how information could lead to cognitive overload [26]. Still, the combined messages resulted in the safest driving behavior. While their focus was semi-autonomous driving, the conclusion that why information causes no negative emotional reaction could indicate that this information is relevant in AVs. Häuslschmid et al. [18] showed the vehicle's current situation interpretation via a world in miniature or a simulated chauffeur avatar. The world in miniature increased trust most, however, participants' opinions varied considerably whether such a visualization is needed.

2.4 Pedestrian Intention Visualization

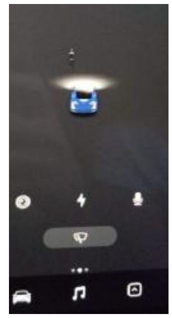
Waymo and Tesla are leading companies regarding AVs [32]. In their dashboard, Tesla visualizes detected vehicles. The system is capable of detecting even multiple cars ahead (see [58]). On highways, vehicles behind the ego-vehicle and vehicles of the oncoming



(a) Motorcycle visualization [9].



(b) Dog recognized as a person in Tesla [47].



(c) Recognized & visualized person in Tesla [59].

(d) Pedestrian visualization on zebra crossing in Tesla [45].

(e) Pedestrian at curb not visualized in Tesla [43].

(f) Pedestrian at curb visualized by Waymo [57].

Figure 1: Visualizations of road users by Tesla and Waymo.

traffic are visualized. The vehicle also detects motorcycles, cyclists, cones [34], people, and animals [47]. Vehicles and people are visualized with the direction they are going or looking at. However, the dashboard visualizes people only if they are on the street [59], but not on the curb [43] even with the "Full Self-Driving Sneak Preview" [33]. This is insufficient as only reacting to pedestrians standing on the street is risky. Drivers are already told to watch out for pedestrians walking on the sidewalk [42]. Waymo presents information on pedestrians as laser points for the passengers. These visualizations are shown in Figure 1, showing the state-of-the-art and highlighting the absence of pedestrian intention visualization in the industry. So far, pedestrian intention was visualized in the context of showing technical feasibility. Kooij et al. [27] proposed a Dynamic Bayesian Network for pedestrian path prediction. Various factors are included: *Situation criticality*, defined by the expected closest distance between pedestrian and vehicle, *pedestrian awareness* of the vehicle (measured via head orientation), and *positioning* to the curbside. They visualize this as shown in Figure 2.

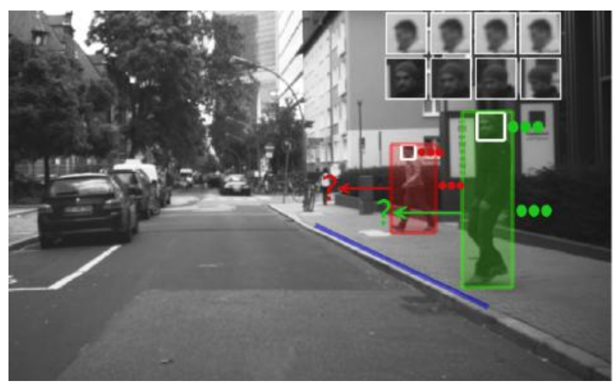


Figure 2: Pedestrian path prediction of Kooij et al. [27]. Tracking bounding boxes of aware pedestrians are visualized green, head detection is visualized via a white box, and the curb with a blue line. Red indicates that the pedestrian is not aware of the oncoming vehicle.

Ghori et al. [14] differentiate between five intention classes: crossing, stopping, starting, turning (based on [50]), and walking along. For them, the most important classes from an Advanced Driving Assistant System point of view are (1) pedestrian crossing or (2) stopping at the curb (see Figure 3).

(a) Orange: Crossing; Yellow: Starting; Blue: Stopping.

(b) Green: Waling-along; Purple: Turning.

Figure 3: Ghori et al.'s [14] proposed visualizations of the intention classes.

Perceptive Automata [2] visualizes pedestrian *Awareness* of the vehicle and *Intention* to cross (see Figure 4). Awareness is visualized by a symbolized eye depicted as more or less opened depending on the detected awareness level of the pedestrian (see Figure 4). The intention to cross is depicted via the number of bars (more bars equal higher intention to cross).

Figure 4: Explanation of the visualization by *Perceptive Automata* as shown in [66].

With regard to pedestrian collision warnings, Kim et al. presented HUD AR systems comparing (1) bounding boxes around detected pedestrians with a virtual shadow, indicating where the pedestrian is estimated to walk to [23] or (2) a "BRAKE" message with the virtual shadow [22]. These systems were evaluated in a high-fidelity driving simulator [23] or in an outdoor study [22]. Compared to the bounding boxes, the four questioned experts liked the lower information density (i.e., lower number of graphics) and reduced mental workload [23]. A possible improvement is more closely connecting the animation with the relevant pedestrian [23]. In the outdoor study [22], the results showed that both systems significantly improve the stopping distance (i.e., participants stopped further away) while the "BRAKE" system resulted in unnecessary hard braking.

3 PEDESTRIAN INTENTION RECOGNITION VISUALIZATION

To systematically evaluate the influence of pedestrian intention visualization on passengers' trust and cognitive load in a highly automated driving setting, we conceptualized possible implementations.

3.1 Concept

We propose to visualize the recognition of the pedestrian and their intention. Following Ghori et al. [14] with the most important intention classes *crossing* or *stopping at the curb* (a subcategory of staying on the sidewalk), we distinguish two levels of information visualization (henceforth called *clarity states*): **two clarity states** with the distinction between intention *recognized* and intention *not clearly recognized* and **three clarity states** where the recognition is further distinguished into *remains on sidewalk* and *crossing*. Only visualizing, for example, intention *recognized* could confuse passengers as a person could just not have been detected. Therefore, **two clarity states** were chosen as minimal requirement. Additionally, we propose to visualize the recognition of the person even if no intention can be derived. This could be the case when the person is still too far away to make predictions. Furthermore, the visualization technique could be altered: **Tablet**-based in the center stack, which is inspired by Tesla, and **AR**-based in which the intention is directly visualized over the respective person. The tablet represents the current state-of-the-art while AR represents the ultimate goal of spatial information distribution. Therefore, these two visualization technologies were chosen. This concept is technology-independently depicted in Figure 5.

3.2 Implementation

To evaluate the concepts, we implemented a VR simulation including traffic and pedestrians using Unity [60] and the asset Windridge City [61]. People are standing in groups and cross the street on crosswalks or via jaywalking. Participants sat in the driving simulator displayed in Figure 7. A steering wheel was installed in front of them. In the simulated world, the participant is seated in a model of the Tesla X (see Figure 6). The car model incorporates a steering wheel as this will likely have to be present until full autonomy is reached.

Our system to visualize pedestrians' intention recognition was implemented as follows: In an area of $r = 35$ m, the system detected every person. As we knew the trajectories, the intention was always clear (relevant for the condition *three intention clarity states*). Within a radius of $r = 30$ m, we displayed the intention of

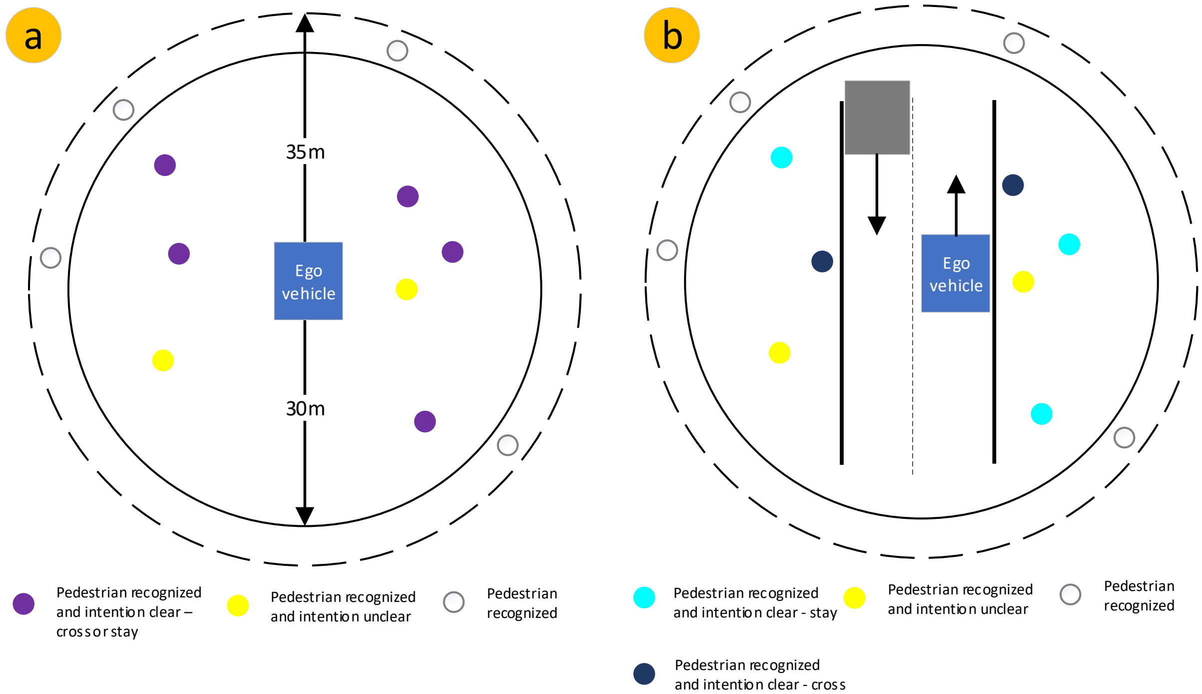


Figure 5: Schematic representation of the visualization. a) For the condition *two system clarity states*, b) for *three system clarity states* with an oncoming vehicle as visualized in the tablet condition.

Figure 6: The interior of the simulated Tesla X alongside the visualizations: *AR three clarity states* (1), *AR two clarity states* (2), *tablet three clarity states* (3), *tablet two clarity states* (4).

the pedestrian depending on the certainty. We explicitly modeled various encounters with pedestrians to indicate the uncertainty of the vehicle. This was intended to simulate an imperfect system. However, these encounters were rare and occurred equally often per condition.

We implemented two visualizations: a tablet-based and an AR-based one. In both systems, color coding was identical. In the tablet version (see Figure 6 (3) and (4)), a graphical representation of the upcoming street was given (in reference to Tesla's Autopilot visualizations). In the AR version, symbols were placed over the recognized people's heads (see Figure 6 (1) and (2)). Circles were used as a consistent representation in both visualizations. In the AR-based version, circles above the pedestrians were chosen to keep spatial proximity while still using relatively small space. Colored bounding boxes, as a different representation, would have needed additional space, resulting in visual clutter. Additionally, this allowed us to include a symbol for the pedestrian. This could be useful if the visualization were to be enhanced for other road users such as cyclists or vehicles. Depending on the study condition (see Section Procedure), two or three intention clarity states were displayed. The visualization of **two intention clarity states** refers to the information *person recognized* and its distinction between *intention clear* (visualized in purple) and *intention unclear* (visualized in yellow). In the level **three intention clarity states** *intention clear* is further distinguished into *intention to cross clear* (visualized in blue) and *intention to stay on sidewalk clear* (visualized in babyblue). These states are depicted in Figure 5. Shades of blue were selected as colors such as yellow or orange carry a warning function, which is unwanted in this case. Still, the colors were highly distinguishable.

4 STUDY

To evaluate the concepts, we designed and conducted a within-subject study with *N*=15 participants. This exploratory study was guided by the following research question:

What impact do the variables "visualization" and "clarity states" have on passengers in an AV in terms of (1) affective state, (2) cognitive load, (3) trust, (4) preference, and (5) capability assessment?

4.1 Apparatus

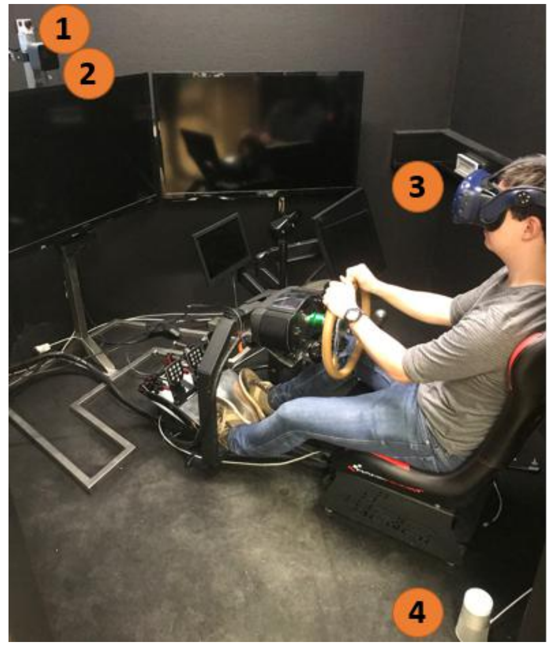


Figure 7: Study setup: camera (1), Vive base station (2), HTC Vive Pro (3) & speaker (4). While this participant holds on to the provided steering wheel, no manual driving was involved.

The study apparatus is shown in Figure 7. We used a simulator for realistic driving especially for the seat to increase immersion. A camera and the HTC Vive base station were put directly in front, a Bluetooth speaker (see Figure 7 (4)) directly behind the participant.

4.2 Procedure

Each participant experienced **five** conditions, a *baseline* with no visualization of the pedestrian intention and a 2 x 2 design (*visualization* with two levels: tablet vs. AR and *system transparency* with two levels: two vs. three intention clarity states; the *independent* variables). The latter resulted in four systems.

Each session started with a brief introduction, signing of the consent form, and a demographic questionnaire. The five conditions were then presented in counterbalanced order. The introduction to the capabilities was given as follows: *You will drive through a city in a Virtual Reality (VR) environment in a highly automated vehicle. The vehicle takes over the transverse and longitudinal guidance. The vehicle tries to determine the intention of nearby passers-by. If this is not finally possible, it will be visualized differently depending on the session.* Participants sat in the simulated vehicle for 5 min per condition and then answered the questionnaires described below. At the end, participants were asked about general feedback. On average, a session lasted 75 min. Participants were compensated with €12.

4.3 Measurements

Objective dependent variables: During each session, the system logged the angles of the view (lateral 0° meaning straight ahead) and the current duration with 10 Hz.

Subjective dependent variables: After each condition, we measured affective state on a 7-point semantic scale using the self-assessment manikin (SAM) [4], cognitive load using the raw NASA-TLX [16] on a 20-point scale, usability with the system usability scale (SUS) [5], and trust in automation using the German version of the Trust in Automation scale of Jian et al. [21] developed by Kraus et al. [30].

Participants were also asked with self-developed single items on 6-point Likert scales how they assessed the capabilities of the system: detection of passers-by, recognition of the intention of passers-by, longitudinal, and lateral guidance. Participants were asked up to what distance passers-by and their intention are detected (< 15 m to > 40 m in steps of 5 m). Additionally, we asked participants after each trial: *How were passers-by visualized who recognized the intention to stay on the sidewalk?*. This served as a manipulation check variable to make sure participants understood the system in this trial correctly. This check revealed that no participants had difficulties in assessing the different colors correctly.

After all five conditions, participants rated their preferences regarding the systems from greatest (*ranking = 1*) to lowest (*ranking = 5*). Open questions regarding feedback and improvement proposals were also asked. Participants rated their immersion using the *Immersion* subscale of the Technology Usage Inventory (TUI) [29]. The usefulness and necessity of both the visualization of detected pedestrians and their intention were measured using single-item ratings on 7-point Likert scales.

4.4 Participants

N=15 participants (4 female, 11 male) were recruited for the experiment. They were on average *M*=25.33 (*SD*=8.17) years old and all hold a driving licence, most of them for at least 3 years (14 participants). 12 are students and 3 employees. On a 5-point Likert scale (*1=strongly disagree*, *5=strongly agree*), participants reported a high interest in AVs (*M*=4.40, *SD*=.74) but were not sure whether such a system would ease their lives (*M*=3.53, *SD*=1.25). The participants believed AVs to become reality by 2029 (10 years from today; *M*=4.07, *SD*=.88). The *Propensity to Trust* subscale of the *Trust in Automation* questionnaire [28] was administered once before and once after all conditions. *Propensity to Trust* was relatively low (*M*=2.40, *SD*=.67) prior to the experiment. A Wilcoxon signed-rank test revealed that, after the simulation, the values for *Propensity to Trust* did not significantly change (*M*=2.40, *SD*=.73). Participants rated their Immersion in a range from 7 to 27, with a mean of *M*=16.47 (*SD*=6.35; min possible is 4, max possible 28). None of the participants had to be excluded from analysis since none reported very low immersion (i.e., <7).

5 RESULTS

Descriptive and inferential statistics are reported. We use Friedman's ANOVAs to compare the five systems as the data is non-parametric [55]. To investigate interaction effects of *visualization* x *clarity states* (both within-group), we disregard the *baseline* and use non-parametric variance analysis (*nparLD* in *R*), a robust method even for small sample sizes [40]. ANOVA-type statistics are reported. For post-hoc tests, we used Bonferroni corrections.

5.1 Affective State

Participants' affective state in terms of arousal was low (range: *M*=2.67, *SD*=1.35 *AR three clarity states* to *M*=3.67, *SD*=1.72 *baseline*), in terms of valence was high (range: *M*=4.33, *SD*=1.59 *tablet two clarity states* to *M*=5.13, *SD*=1.30 *AR three clarity states*), and in terms of dominance was low (range: *M*=2.27, *SD*=1.62 *baseline* to *M*=2.80, *SD*=1.86 *AR two clarity states*).

Friedman's ANOVAs showed no significant difference in the mean ratings in dominance, valence, or arousal.

5.2 Cognitive Load

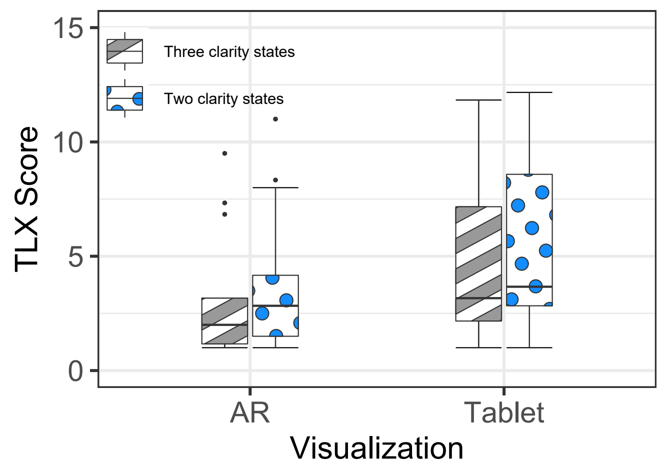


Figure 8: Main effects on TLX score of *visualization*. AR reduces cognitive load.

Cognitive load was measured using the raw NASA-TLX. Overall scores were low for all conditions (range: *M*=2.99, *SD*=2.70 *AR three clarity states* to *M*=5.51, *SD*=3.93 *tablet two clarity states*).

A Friedman's ANOVA showed a significant difference in the mean overall scores (χ^2 (4)=20.7, *p*<.001). Post-hoc tests showed that the *AR three clarity states* system received significantly lower TLX scores compared to the *tablet two clarity states* and the *tablet three clarity states* systems. The non-parametric variance analysis showed a significant main effect on the overall score of *visualization* (*F*=13.03, *df*=1, *p*<.001; see Figure 8).

5.3 Trust in Automation

The reported trust [21] was in the range of *M*=3.86 (*SD*=1.46, *baseline*) to *M*=5.33 (*SD*=1.68, *AR three clarity states*).

A Friedman's ANOVA showed a significant difference in the mean rankings for the participants (χ^2 (4)=14.0, *p*=.007). Post-hoc tests showed that the *AR three clarity states* system received significantly higher hyratings compared to the *baseline*. The non-parametric variance analysis showed a significant main effect on

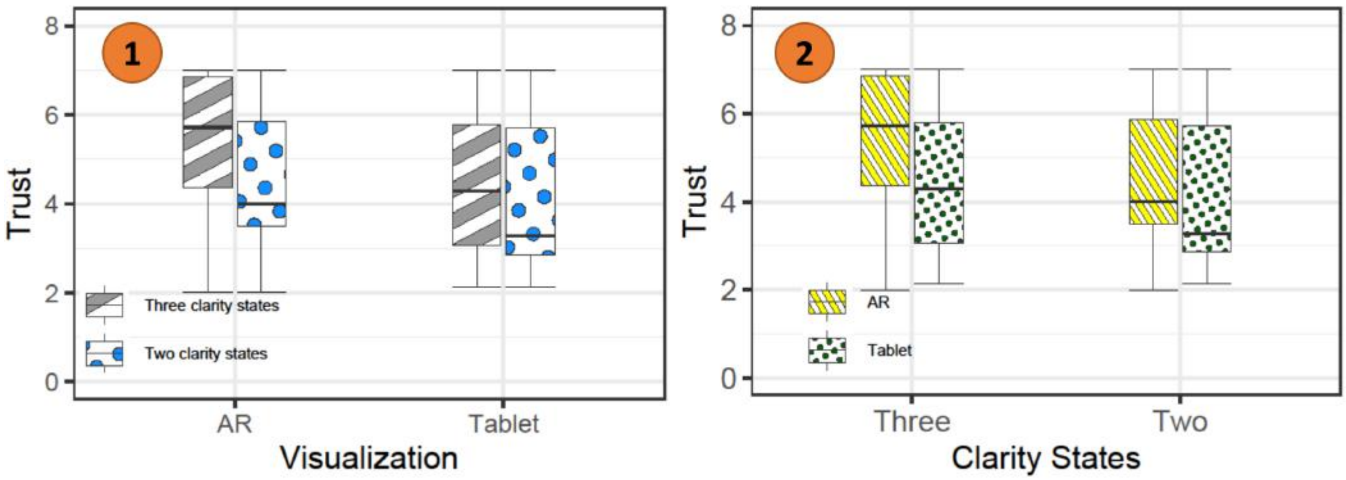


Figure 9: Main effects on Trust score of (1) *visualization* (AR increases Trust) and of (2) *clarity states* (three clarity states increases Trust).

the trust score of *visualization* (F=3.86, df=1, p=.049; see Figure 9 (1)) and *clarity states* (F=4.43, df=1, p=.04; see Figure 9 (2)).

5.4 Capability Assessment

The capabilities of the simulated AV were rated with respect to detection of pedestrians, recognition of pedestrians' intention, and lateral and longitudinal control. The assessment of detection of pedestrians went from M=4.13 (SD=1.77; *baseline*) to M=5.67 (SD=.62; *AR three clarity states*). Intention recognition was also rated lowest for the *baseline* (M=3.13, SD=1.17) and highest for the *AR three clarity states* system (M=5.00, SD=1.13). Values for lateral and longitudinal control were all relatively high (the mean being ≈5.00).

Asked about the pedestrian recognition capabilities in terms of distance (i.e., m), participants rated the *baseline* lower (M=2.80, SD=1.97) than the visualized systems (*tablet two clarity states* being rated the highest; M=4.53, SD=1.77). The same is true for the intention recognition (*baseline* M=1.67, SD=1.11 compared to M=2.87, SD=1.64 for *tablet two clarity states*). The correct value for pedestrian recognition is **5** (equalizing 35 m) and for the intention recognition **4** (equalizing 30 m; see Section Implementation).

A Friedman's ANOVA showed a significant difference in the mean rankings for the participants in terms of detection of pedestrians (χ^2 (4)=21.2, p<.001). Post-hoc tests showed that the *baseline* received significantly lower ratings than the *AR three clarity states* system. The same holds true for the intention recognition assessment (χ^2 (4)=14.3, p=.006) with post-hoc tests showing significantly lower ratings for the *baseline* compared to the *AR three clarity states* system. No significant differences were found for lateral and longitudinal control. Friedman's ANOVA showed significant differences for the distance of pedestrian recognition (χ^2 (4)=16.6, p=.002) and the distance of pedestrians' intention recognition (χ^2 (4)=12.8, p=.01). Post-hoc tests only showed significant differences for the distance of pedestrian recognition between the *baseline* and the *tablet two clarity states* system, the latter being rated as having significantly higher recognition capabilities.

5.5 System Preferences

The *AR three clarity states* system received rankings indicating the highest preference, i.e., the lowest mean (M=.83, SD=1.20). The remaining ranking was as follows: *tablet two clarity states* (M=4.07, SD=.70), no visualization (*baseline*; M=4.00, SD=1.36), *tablet three clarity states* (M=3.27, SD=1.16), *AR two clarity states* (M=2.47, SD=.83).

A Friedman's ANOVA showed a significant difference in the mean rankings for the participants (χ^2 (4)=34.4, p<.001). Post-hoc tests showed that, compared to the *AR three clarity states* system, all other systems except the *AR two clarity states* system were rated significantly worse.

5.6 Reasonability and Necessity

The mean value for the single item rating the visualization of the *intention* as reasonable on a 7-Likert scale was very high (M=6.40, SD=1.18) and high for the rating as necessary (M=5.40, SD=1.64). The mean ratings for the visualization of the recognition were lower, however, still high. M=5.73 (SD=1.53) for being reasonable and M=5.20 (SD=2.01) for being necessary.

5.7 Open Feedback

In general, participants highlighted the need for and benefits of such a visualization ([P3]: "So in most cases, where the intention has been recognized, he [the user] does not have to worry about the pedestrian."). [P11] also emphasized the visualization with three clarity states: "that 3 different states were displayed, you knew exactly what the system detected, you could easily focus on the states, especially when people were crossing the street". Most negative associations were mentioned with the tablet ([P2]: "The visualizations on the display are difficult to comprehend as the pedestrian in the real world must always be searched for to make comparisons, but there is sometimes not enough time for this") and the *baseline* ([P8]: "No visualization creates uncertainty"). [P14] also criticized the visualization with two clarity states as "The solution without visualization of the pedestrian intention (i.e., only purple, yellow, and unfilled circle) does not provide any information about what the pedestrians want to do. So this information is useless from my point of view, because if the intention is wrongly recognized (which can always happen) a driver might not be able to intervene fast enough.". Regarding improvements, participants suggested to "Hide pedestrians behind the vehicle on the tablet" [P1] and to reduce the visualizations for when "a dangerous situation (intention not recognized) exists" [P15]. Regarding the need for such a visualization, [P14] mentioned:

> "From my point of view, a visualization of the pedestrian intention makes sense, especially with the introduction of the first autonomous vehicles. With this, the fear of the vehicle can be taken away from the driver/user and the feeling of being in control can be transmitted."

6 DISCUSSION

Overall, the *AR three clarity states* system had the lowest cognitive load ratings, highest trust and capability ratings concerning pedestrian detection and pedestrians' intention detection, and was the most preferred option. This is in line with studies that show that transparent systems [8, 26] as well as AR systems [18, 65] lead to increased trust, acceptance, and perceived safety among drivers. Participants also rated the visualization of pedestrians' intentions as highly necessary and reasonable at least in the introductory phase while, in previous studies, participants did not always agree on the need for visualizations [18]. Still, there are some points to discuss.

6.1 Visual Aesthetics

Regarding the visual aesthetics of the concepts, various alterations are possible. [P8] stated that "Possibly rethink the color scheme, e.g., people crossing the street in a signal colour". However, this was explicitly omitted to avoid the notion of *good* or *bad* signals, which should be reserved for critical incidents. In our simulation, all symbols were of equal size. Depending on the certainty of the vehicle of their pedestrian (intention) recognition, this size could vary. Additionally, groups of people could be combined into a single symbol to avoid visual cluttering and to, therefore, reduce cognitive load. This would be possible, for example, for people standing and chatting. A single person leaving the group to cross a street would be even more highlighted with such an approach.

The Halo Effect [39] is a widely known cognitive bias based on which positive impressions of system attributes lead to positive impressions of other attributes. This Halo Effect seems to be **not** at work: with the more sophisticated looking AR systems, the ratings for the pedestrian and intention recognition were high but the ratings for lateral and longitudinal control remained about the same.

Tablet-based systems were rated significantly worse. The question arises whether the visualization is the reason for this or whether the need for a mental mapping between dots on the simulated tablet and the real-world is the cause for the dislike. While this cannot be answered for sure, such a mapping is necessary even if the visualization changed.

Adding additional crossing-behavior related properties of pedestrians such as age [46] were discarded with regard to cognitive overload. While these properties must be included in the pedestrian-assessment by the AV, we hypothesize that this information is less relevant for the passenger.

Compared to the virtual shadow [23], our visualization introduces a higher number of graphics which could lead to higher visual clutter [13] and a less accurate estimation of where the pedestrian is headed to. However, it is not clear that such an estimation is accurately possible. Additionally, our visualization is intended for AVs, therefore, intervention by the human passenger is not necessary. Our system is intended to convey the capabilities of the AV instead of aiding the driver to perform the driving task.

6.2 Pedestrian Intention Visualization for Takeovers

While the described system is intended for highly automated vehicles, benefits for situation awareness could be applied to handovers in lower automation levels (e.g., SA Level 3 [56]). The visualization for this could vary depending on the technical capabilities of the system (see [62]). With lower capabilities, the current visualization of all recognized pedestrians and their intention could be visualized. In higher sophisticated systems, only potential threats could be (and then more prominent) visualized. For this, lingering arrows could be used. Another possible approach could be to include an attention-grabbing mechanism to alert the user.

6.3 Practical Implications

For the introduction of AVs, it seems beneficial to display relevant information to the user of the vehicle to increase trust. While the AR systems were favored, the technical feasibility of this technique is (today) questionable. The *tablet three clarity states* system was, however, also preferred to the *baseline*. This could indicate that visualizing pedestrians and their intentions in a center stack or a HUD could increase trust. Tesla already shows pedestrians **on** the street and most likely uses algorithms to recognize intention. Therefore, the step towards visualizing the intention of pedestrians on sidewalks seems feasible and desirable. The *tablet two clarity states* system was preferred less than the *baseline* (i.e., no visualization). One reason could be that the aforementioned mapping is too arduous for the additional information gained (as the *tablet three clarity states* system was ranked higher). However, we assume most of the dislike for tablet-based systems comes from the needed mapping. Such visualized information should, therefore, be presented as close to the object as possible (e.g., via a HUD).

7 LIMITATIONS

The number of participants in the study was of moderate size (N=15). Transferability to a real-world scenario is restricted due to the usage of a VR simulation. In the simulated drives, all pedestrians are recognized up to a distance of 35 m. However, errors such as pedestrians not being detected correctly or with an incorrect intention can occur. In case of failure of the system or a (perceived) error, overtrust in technology can lead to over-distrust. Therefore, this experiment should be repeated with failure of the presented visualization to investigate this effect. In addition to system errors, situational factors such as distracted or blind pedestrians can induce uncertainty in the passenger. The impact of these factors on passengers' perception and trust should, therefore, be examined in future studies. Also, subjective ratings were the sole dependent measures.

8 CONCLUSION AND FUTURE WORK

This work showed the lack of visualization in the context of pedestrian (intention) recognition in current vehicles (e.g., Tesla or Waymo). Afterwards, technology-dependent solutions were proposed: a tablet version that seems possible for current vehicle models and an AR system that could be possible in the future. A controlled experiment in VR (*N*=15) showed that the *AR three clarity states* system was rated best. Almost all models were rated better than the baseline, which is the current standard. In the future, the tested systems should be investigated under other conditions: failure of the detection system should be investigated and a comparison to light-band systems [64] should be undergone.

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