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Interaction between pedestrians and automated vehicles: Exploring a motion-based approach for virtual reality experiments

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ABSTRACT

External human machine interfaces (eHMI) might contribute to an enhanced traffic flow and road safety by providing relevant information to surrounding road users. To quantify the effect of eHMI on traffic flow, the majority of studies required participants to indicate their crossing decision in an explicit manner, such as pressing a button. While this approach proved to be efficient, the transfer to real-world behavior is unclear. Here, we propose a more realistic, motion-based approach allowing pedestrians to actually cross the road in front of a vehicle in a virtual reality environment. Participants ($N = 51$) encountered simulated automated vehicles (AVs) in two scenarios. We investigated the effect of different eHMIs on traffic flow and road safety. Pedestrianś body movements were obtained using a motion capturing system with six sensors. Our approach was validated using a two-step procedure. First, we assessed crossing behavior and subjective safety feeling while approaching AVs with and without eHMI. Second, we tested to which extent objective crossing behavior matched self-reported safety feeling. For this purpose, we evaluated if subjective safety feeling can be reliably predicted from actual crossing behavior using a functional data analysis. The proposed motion-based approach proved a valid investigation method for eHMI designs. The results indicated that eHMIs have a beneficial effect on traffic flow and road safety. Regarding traffic flow, participants crossed the road earlier and felt significantly safer when encountering an AV with an eHMI compared to no eHMI. In addition, in situations in which only some of the AVs were equipped with an eHMI, participants' crossing behavior and safety feeling became more conservative for encounters without eHMI, indicating higher road safety. Further, subjective safety feeling was significantly predicted from actual crossing behavior. These findings highlight that eHMIs are beneficial for pedestrians' crossing decision, both from an objective and subjective perspective.

1. Introduction

Communication between road users is essential to ensure traffic flow and road safety (Färber, 2016). In conventional road traffic, drivers rely on various formal methods such as turn signals, brake lights and emergency lights to communicate with surrounding road users. Beside these formal methods, additional informal methods like facial expressions, hand gestures and eye contact are used to enhance traffic flow and improve road safety (Rasouli & Tsotsos, 2019; Šucha, 2014). In North America and Europe these means of

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communication become especially important at ambiguous situations which are not strictly regulated by legal provisions, such as a non-signalized crossing (Färber, 2016).

Based on current market forecasts, vehicles at different automation levels will dominate the future transportation system (Litman, 2020). With automated vehicles (AV) of SAE Level 4 (high driving automation) and 5 (full driving automation), the complete dynamic driving task is performed by the automation system and no driver is required to take control over the driving task (SAE International, 2018). However, experts expect a long transition period in which vehicles of different automation levels have to share the same traffic space (Litman, 2020; Sivak & Schoettle, 2015). While AVs can communicate by formal means, informal means of communication with a driver will no longer be available. Among road users, this change will largely affect pedestrians, who often assure their road safety through interpersonal interaction with the driver (Šucha, 2014). Accordingly, previous studies showed that pedestrians feel uncomfortable when they are not able to communicate with the driver (Langström & Malmsten Lundgren, 2015; Risto, Emmenegger, Vinkhuyzen, Cefkin, & Hollan, 2017; Rothenbuecher, Li, Sirkin, Mok, & Ju, 2016).

At least at initial stages of mixed traffic environment, pedestrian's sense of comfort may be impaired because of concerns about the technology's safety (Eng, 2017). The introduction of AVs without a deeper social understanding of the communication between pedestrian's and drivers might lead to misunderstandings that can potentially result in traffic accidents and malicious behavior (Rasouli & Tsotsos, 2019). Therefore, adequate communication concepts between an AV and pedestrians are needed in order to ensure traffic efficiency and safety for all road users (Schneemann & Gohl, 2016). This is especially critical in ambiguous situations which can only be solved by using informal communication strategies (Färber, 2016). Research and technical development focus on the application of external human–machine interfaces (eHMI) for AVs to address the communication problems pedestrians might soon face. These external interfaces comprise of visual indicators in form of LED displays (Othersen, Conti-Kufner, Dietrich, Maruhn, & Bengler, 2019), lighting elements (Faas, Mathis, & Baumann, 2020) or projections (Nguyen, Holländer, Hoggenmueller, Parker, & Tomitsch, 2019). An eHMI might communicate by presenting information about the driving mode of the vehicle, its intention or its perception of the surrounding (Schieben, Wilbrink, & Kettwich, 2018). While various studies have shown a beneficial effect of eHMIs on perceived safety (Song, 2018), comfort (Ackermann, Beggiato, Schubert, & Krems, 2019) und user experience (Faas, Mattes, Kao, & Baumann, 2020), the question if eHMIs can contribute to an improved traffic flow and road safety is still not satisfactorily answered (Faas et al., 2020; Othersen et al., 2019). In order to investigate the effect of eHMI on traffic flow, previous research relied on subjective self-reports. In our study, we aim to extend this research and propose a motion-based assessment approach based on actual crossing behavior. In the following, we first present an overview of previous research investigating the effect of the presence of an eHMI on subjective measures. Afterwards, we discuss studies incorporating the impact of eHMIs on traffic flow and road safety and finally introduce our study.

1.1. Previous research on pedestrian-automated vehicle interaction

Numerous eHMI concepts for AVs have been developed for substituting the communication with a human driver (Schieben et al., 2018). The majority of previous studies emphasized the demand of new forms of communication in order to enhance the pedestrians' subjective safety feelings. Therefore, the pedestrians' need to communicate with a driver is reflected in their safety rating (de Clercq et al., 2019). Studies evaluated the effect of eHMIs on subjective safety feeling in two different forms. On the one hand, participants are required to give self-reports regarding trust and subjective safety using questionnaires (Böckle, Brenden Pernestål, Klingegård, Habibovic, & Bout, 2017; Habibovic, Andersson, Malmsten Lundgren, Klingegård, Englung, & Larsson, 2019). On the other hand, subjective safety feeling was continuously assessed as a function of the AVs' distance to the pedestrian (Dey, Martens, Eggen, & Terken, 2019; Walker et al., 2019). For instance, in a virtual reality experiment, de Clercq et al. (2019) instructed participants to continuously rate their feeling of safety to cross while approaching an AV using a handheld button.

Despite different forms of assessment, the conclusion in the most studies are similar. While approaching an AV, participants preferred having an eHMI compared to not having an eHMI present (de Clercq et al., 2019). The application of an eHMI positively influenced subjective safety feeling (Habibovic et al., 2019), comfort (Böckle et al., 2017), trust (Faas et al., 2020) and user experience (Stadtler, Cornet, Theoto, & Frenkler, 2020). Beside these beneficial effects of eHMI application, its comprehensibility and perceptibility seem to differ depending on the design of the eHMI. First, icon- and light-based designs can be distinguished, where an icon or a LED bar are displayed outside the vehicle. While icon-based designs proved to be intelligible, light-based designs were not intuitively understandable and needed to be learnt beforehand (Habibovic et al., 2019; Hensch, Neumann, Beggiato, Halama, & Krems, 2019). Second, each design can be presented in a static and a dynamic manner. Dynamic designs were evaluated as clearly perceptible, whereas the AVs' future states and maneuvers can less easily be derived from static ones (Othersen et al., 2019; Stadtler et al., 2020).

While previous research emphasized the demand of eHMI to enhance pedestrians' safety feeling, some studies additionally assessed the effect of eHMI on traffic flow (Chang, Toda, Sakamoto, & Igarashi, 2017; de Clercq et al., 2019; Eisma, van Bergen, ter Brake, Hensen, Tempelaar, & de Winter, 2020). Generally, traffic flow was defined as number of road users passing by per time unit (Hoogendoorn & Knoop, 2013). The studies usually utilized either desktop computers or virtual reality pedestrian simulators to analyze pedestrians' reactions when encountering an AV. Different methodological approaches were used to operationalize traffic flow. Some studies captured the participants' binary decision to cross the road in front of an approaching AV. For example, Song (2018) conducted an interactive online survey, in which videos of AVs with an eHMI were presented. After each video, participants had to indicate if they would cross the road or let the AV pass by pressing the space bar. This approach only assessed if participants would cross, but not when exactly they would cross.

Other studies measured the so-called crossing initiation time (CIT) by determining the exact time point pedestrians would cross. Thereby, two main approaches can be distinguished: unnatural and natural ones. Unnatural approaches require participants to indicate when they would cross the road by pressing a button (Chang et al., 2017), raising a hand (Fuest, Michalowski, Träris, Bellem, &

Bengler, 2018) or taking a step backward (Rodríguez Palmeiro, van der Kint, Vissers, Farah, de Winter, & Hagenzieker, 2018). For instance, Chang et al. (2017) instructed participants to indicate their decision to cross by pressing a button on a motion controller. Results indicate shorter reaction times when an eHMI was applied in contrast to when no eHMI was displayed. The authors concluded that the eHMI enabled pedestrians to already make a decision to cross, before the vehicle came to a stop, resulting in enhanced traffic flow. While this approach allows for rapid prototyping and provides safety for participants, it may lack realism (Rouchitsas & Alm, 2019). Participants were required to indicate their decision to cross, but do not actually cross the road, which might limit the ecological validity (Baumeister, Vohs, & Funder, 2007; Holt & Laury, 2002). Natural approaches require participants to actually cross the road. In terms of ecological validity, measuring CIT based on the actual crossing behavior constitutes to the best approach. Crossing the road can be seen as a ritualized behavior (Rietveld, 2008). In road traffic, pedestrians normally act appropriately, without reflecting on their behavior. The crossing decision is not based on explicit reasoning, but a form of embodied intelligence (Rietveld, 2008). It can be argued that pedestrians initiate crossing once they feel safe to cross. Currently, only a few virtual reality studies (Kooijman, Happee, & de Winter, 2019; Othersen et al., 2019) and field studies using physical prototypes (Clamann, Aubert, & Cummings, 2016; Faas et al., 2020) have investigated the effect of eHMIs on pedestrians' actual crossing behavior. One reason for this might be that the crossing task is seen as a safety–critical task and therefore raises ethical concerns. In a virtual reality experiment, Othersen et al. (2019) contrasted a baseline condition without eHMI with four eHMIs, varying in type (icon-based vs. light-based) and dynamics (static vs. dynamic). Pedestrians were instructed to make street-crossing decisions while an AV with one of the eHMIs was approaching. To explore the effect of eHMIs on traffic flow, CIT was assessed using motion tracking. CIT was defined as the time difference between vehicles stop and the pedestrians' crossing initiation, indicated by a head movement 70 cm in crossing direction. All eHMIs proved to contribute to an optimized traffic flow, as shown by shorter CIT compared to the baseline condition without eHMI. However, no significant differences in CIT were found between the different eHMIs. Similar, in a field experiment, Faas et al. (2020) examined the effect of different eHMIs on participants' subjective feelings, crossing behavior and underlying attitudes. To examine whether eHMI can contribute to an optimized traffic flow, participants' crossing onset and crossing duration was analyzed using on-site camera recordings. While eHMIs showed a beneficial effect on subjective feelings, no effect on crossing behavior was found. Using a similar approach, Clamann et al. (2016) failed to show any significant effects of eHMIs on crossing behavior. In this study, retrospective interviews showed that 76% of participants recognized the eHMIs, yet only 12% declared that the eHMIs had an impact on their crossing decision. Summarizing, previous studies used different methodologies to measure crossing behavior such as video coding procedures (Faas et al., 2020) and motion tracking (Othersen et al., 2019). Thereby, results differ and thus the impact of eHMIs on traffic flow is not yet clear.

In addition to traffic flow, the application of an eHMI might affect pedestrians' road safety. In a mixed traffic environment, in which vehicles with different automation levels operate simultaneously, the reaction to the absence of an eHMI represents an important aspect of road safety (Petzold, Schleinitz, & Banse, 2017). Since only some of the vehicles will be equipped with an eHMI, pedestrians cannot rely on their information. This fact may influence pedestrians' reaction to encounters without an eHMI. In a monitor-based study, Petzold et al. (2017) instructed participants to watch videos of approaching vehicles and press a button whenever they have recognized the deceleration of the vehicle. Results suggest that in a scenario in which a portion of decelerations was accompanied by an eHMI, the participants' reaction times become more conservative for decelerations without eHMI. The authors argued that the conservative behavior might be an indicator for a potential road safety effect of eHMI.

In summary, literature suggests that eHMI applications enhance subjective safety feeling (e.g., de Clercq et al., 2019). Particularly, pedestrians' feeling of safety increased for AV-encounters with eHMI compared to AV-encounters without eHMI. Previous studies regarding the effect of eHMIs on traffic flow reached different conclusions. In the majority, participants' decision to cross was captured in an explicit manner, for example via pressing a button (e.g., Chang et al., 2017). Few studies have assessed the actual crossing behavior of pedestrians while encountering an AV (Clamann et al., 2016; Faas et al., 2020; Othersen et al., 2019). While studies on decision making found significant differences between AV-encounters with and without eHMIs, behavioral studies failed to find meaningful differences. Furthermore, previous research suggests that eHMI can contribute to an optimized road safety. However, to the best of our knowledge, only one monitor-based study was conducted to investigate the effect of eHMIs on road safety (Petzold et al., 2017). This motivated our research effort to develop a new methodological approach based on actual crossing behavior to evaluate the effect of eHMI on traffic flow and road safety.

1.2. Rationale

In this study, we propose a motion-based approach to investigate whether eHMIs can support pedestrians in their interaction with AVs. This approach actually requires pedestrians to cross the road in front of an AV. We conducted a virtual reality experiment in which participants encountered simulated AVs either equipped or not equipped with an eHMI. Four eHMIs were contrasted against a no eHMI condition. The experiment was divided in two blocks. In block A, no eHMI was displayed. In block B, some of the AVs communicated via an eHMI. To increase transferability of results, we investigated two different scenarios, a daytime and a nighttime scenario. The study applied a mixed-method approach for data analysis that includes pedestrians' crossing behavior and their subjective safety feeling while crossing. Specifically, we propose a simple and precise histogram-based thresholding approach for the calculation of CIT and mean walking speed.

In order to validate our approach, we used a two-step procedure. First, we wanted to extend previous research by examining whether eHMI can contribute to an enhanced traffic flow and road safety. To assess the effect of eHMI on traffic flow, we compared pedestrians' crossing behavior and subjective safety feeling in block B for encounters with and without eHMI. It was hypothesized that eHMI had an effect on pedestrians' crossing behavior in terms of a lower CIT and higher mean walking speed compared to no eHMI.

According to previous findings, it was hypothesized that participants feel safer when encountering an AV with an eHMI compared to not having an eHMI present. In order to explore the effect of eHMI on road safety, we investigated the extent to which pedestrians' reactions for encounters without eHMI differ between blocks. According to the results of Petzold et al. (2017), we hypothesized that in situations in which only some of the AVs are equipped with an eHMI, participants become more conservative for encounters without eHMI. Accordingly, a higher CIT, lower mean walking speed and subjective safety feeling were predicted. Second, we tested to which degree objectively measured crossing behavior matches pedestrians' subjective safety feeling. Using a functional data analysis, we evaluated if subjective safety feeling for each trail can be reliably predicted from actual crossing behavior.

2. Methods

2.1. Participants

Participants were recruited randomly from the pool of Porsche employees in Weissach, Germany. They were required not to have any musculoskeletal diseases due to the use of a motion capturing system. Initially, a total sample of 52 participants took part in the present study. However, some data had to be excluded according to pre-defined criteria: (1) physical constraint due to motion capturing system and (2) complete motion data recordings per experimental trial. In accordance to (1), $n = 1$ participant had to be excluded. According to (2), 37 of a total of 1224 experimental trials were excluded due to poor detection rates. As the 37 experimental trails were missing completely at random for 16 participants, we decided not to drop all trials of concerned subjects from the analysis. The final sample of $N = 51$ consisted of 15 females and 36 men. In general, the sample included a broad range of different age categories. There were 22, 21, 5, 1, 2 participants in the 21–30, 31–40, 41–50 und 51–60 age categories. The sample was skewed in terms of education, since 84% of the subjects had at least a high school degree or even a university degree. Nearly one out of four declared having participated in virtual reality experiments before.

2.2. Apparatus

The study was carried out in a virtual reality pedestrian simulator at the Porsche Development Center in Weissach, Germany. The pedestrian simulator consisted of a standard HTC VIVE Pro setup, which included a HTC VIVE Pro head-mounted display with a resolution of 2880 × 1600 pixels and infrared trackers (HTC Corporation, 2018b). Cinema 4D (Version R20; Maxon, 2018) and Unity3D (Version 2018.3.7f1; Unity Technologies, 2018) were used as software for simulation. The simulation was run on a desktop with Intel® Xeon® Gold 6134 CPU processor (3.19 GHz), 192 GB RAM, NVIDIA Quadro RTX5000 graphic card with 16 GB VRAM and a Windows 10 Enterprise operating system. For improved immersion, real environmental sounds stemming from the laboratory were suppressed and driving sounds from the virtual world were emitted via headphones. The volume of the driving sounds depended on the distance and the velocity of the approaching vehicle. The fully immersed virtual environment represents an inner-city traffic scene. The road cross-section was designed according to the German standard with a width of 3.35 m. The participants could move around freely within an area of nearly 5 × 3 m. A start and target position indicated by yellow circles on the ground highlighted the end of the accessible area, as shown in Fig. 1. In order to raise the ambiguity of the traffic situation for participants, it was decided not to use a signalized crosswalk.

Participants' body locations were obtained using a motion capturing system consisting of five HTC VIVE wireless trackers (HTC Corporation, 2018a) and the HTC VIVE head-mounted display (HTC Corporation, 2018b). The trackers were attached on five body locations to track and calculate their motion using specific tracker belts: upper arms, belly and ankles (see Fig. 2). Their position and orientation were determined with the help of four VIVE base stations (HTC Corporation, 2018b). The wireless trackers provided recordings of motion data with a system end-to-end latency of 22 ms (Niehoster, Li, & Lappe, 2017). The sample rate of the motion data was set to 25 Hz. Before motion data collection, a calibration routine was carried out carefully for every participant. Software

Fig. 1. Virtual traffic environment. Yellow circles indicated the start (S) and target (Z) position. The virtual board on the other side of the road allowed participants to rate their safety feeling by selecting one of the black buttons with their index finger. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

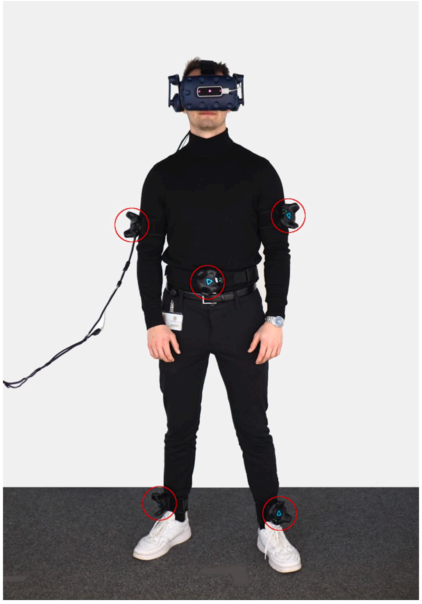

Fig. 2. Positions of HTC VIVE wireless trackers on the body locations.

developed in-house was used to synchronize on-line motion data of the body locations and store the entire output in a data file.

2.3. Procedure

Subjects participated individually in the study. On arrival, they were introduced to the objective and the procedure of the study and were familiarized with the virtual reality pedestrian simulator. The first part of the study consisted of a virtual reality experiment. Prior to the experiment, participants were instructed to experience the virtual traffic scenario as a pedestrian standing on a pavement in front of a one-way urban road. They were introduced to the definition of fully automated driving (Level 5) according to SAE International (2018) and were told that exclusively AVs would approach from left. Additionally, they were notified that all vehicles are equipped with a display on their radiator grill, which enable them to communicate with their environment. However, no information about the eHMI variants was provided to avoid hypothesis-confirming behavior. After signing a consent form and an initial calibration routine, participants completed a practice trial to get used to the virtual traffic environment and the motion capturing system. During this practice trial, they trained crossing the road in front of stationary vehicles until reporting to feel comfortable with the crossing task. Afterwards, participants completed the actual experiment. Each participant experienced 24 trials in total. The experiment included two blocks, five eHMI conditions and two scenarios. In block A, participants initially performed four trials without any eHMI as a reference. In block B, they completed additional 20 trails, 16 with and four without an eHMI. Block A was always followed by block B, while eHMI conditions and scenarios were randomized within blocks. For each trial, participants were placed on a starting position. AVs approached from left with a constant speed of 40 km/h. The starting point of all vehicles was in a virtual distance of 40 m from the participants. Following traffic showed pre-defined gap distances which adopted to the current speed of the direct leading vehicle. Gap distances were selected such that a braking maneuver of the yielding vehicle was necessary to cross the road safely. About every eighth vehicle in the line of traffic started braking in distance of 20 m at a constant deceleration rate of -3.5 m/s^2 and, where appropriate, concurrently displayed an eHMI on the radiator grill. Finally, it stopped 2.3 m in front of the participant. The number of passing vehicles was pseudorandomized so that every eighth vehicle ($SD = 3$) was breaking. Non-yielding vehicles were included to prevent participants from anticipating vehicles' braking actions. The participants were given the task to cross to the other side whenever they felt safe to cross once the first AV had passed them. After reaching the pavement on the other side, they were asked to press a button on a virtual board to rate their subjective feeling of safety while crossing. After returning to the starting position, the next trial started. During the experiment, participants were instructed to minimize interactions with the experimenter to reach a sufficient immersion in the virtual environment.

The second part of the study included completing the following questionnaires on the computer: Igroup Presence Questionnaire (Schubert, Friedmann, & Regenbrecht, 2001), the Misery Scale (MISC; Bos, Mackinnon, and Patterson, 2005), User Experience Questionnaire Short (UEQ-S; Schrepp, Hinders, and Thomaschewski, 2017) as well as a demographic questionnaire. Each session lasted approximately one hour of which the introduction and virtual reality section took about 40 min and the follow-up questionnaire 20 min.

2.4. Experimental design and conditions

The virtual reality experiment was designed as a 2 × 5 × 2 incomplete repeated measures design with the factors block, eHMI and scenario. All factors were within-subject factors. The experiment was divided into two blocks (factor block). During block A, no eHMI was displayed while breaking and participants had to derive the intention of the encountering vehicle solely from the driving behavior. In block B, eHMIs were presented in 80% of braking maneuvers. In 20% of braking operations no eHMI was activated. Each participant first completed block A and then block B. However, scenario and eHMIs were randomized with a Latin square design such that each participant viewed the scenarios and eHMIs in different order within each block. The experimental design made it possible to quantify the effect of eHMIs on traffic flow by comparing participants' reactions to braking maneuvers with and without eHMIs within block B. Furthermore, it could be investigated to what extent the fact that only some of the AVs were equipped with an eHMI might have had an impact on pedestrians' road safety. Therefore, participants' reactions for encounters without eHMI were compared between block A and block B. As proposed by Petzold et al. (2017), more conservative reactions for AV-encounters without eHMI in block B compared to block A would indicate a higher road safety.

To account for potential differences in the comprehensibility of communication strategies, four different eHMIs were examined in this study (see Fig. 3). Furthermore, a no-eHMI condition was included (factor eHMI). For displaying the eHMIs, a virtual display with 22 cm high was integrated into the radiator grill of the vehicles. In previous research, this position turned out to be suitable for mounting a communication device (Eisma et al., 2020). The first eHMI type consisted of a lighting element, which was concentrically arranged on the display. This light-based design concept geared to previous examined lighting design for vehicle-to-pedestrian-communication (e.g., Langström and Malmsten Lundgren, 2015). In the static variant a virtual LED-bar lighted up simultaneously to the braking initialization 20 m away from the pedestrian and was turned off after crossing. The design recreated a frontal braking light communicating the vehicles intention to stop (Antonescu, 2013; de Clercq et al., 2019; Petzold et al., 2017). In the dynamic variant, the LED bar was displayed as a simple chase light with a one-direction running pattern from left to right indicating the pedestrians' crossing direction. This eHMI approximated already proposed concepts in the literature (Habibovic et al., 2019; Langström & Malmsten Lundgren, 2015; Mahadevan, Somanath, & Sharlin, 2018). As the second eHMI type, an icon-based design was used. In the static variant, an icon of vehicle with a stop line in front was presented symbolizing the intention to stop for the pedestrian. In the dynamic variant, a walking man animation was shown. The crossing direction was indicated by the walking direction of the walking character. The eHMIs were displayed in white color for best contrast performance and to avoid attentional bias due to coloring. They were presented concurrently with the initiation of the breaking action at a virtual distance of 20 m from the pedestrians. In the baseline condition, no eHMI was displayed and the participants had to derive the vehicles' intention only from its movement.

To increase the transferability of the study results, a daytime and nighttime scenario (factor scenario) were included into the experimental setup. Previous literature suggests that lighting conditions affect pedestrians' crossing behavior in various forms (Rasouli & Tsotsos, 2019). For example, the illuminance of the road influence the perception of speed (Shi, Wu, & Qian, 2020). Furthermore, pedestrians' visual functions are impaired at nighttime, which might have an effect on their crossing decision (Rasouli & Tsotsos, 2019).

2.5. Dependent variables and materials

2.5.1. Subjective safety

Subjective safety feeling was assessed with a single item and the following wording: "How safe did you feel while crossing the road?" After each trial, participants had to evaluate their subjective safety feeling using a Likert scale ranging from 1 (*not at all*) to 5

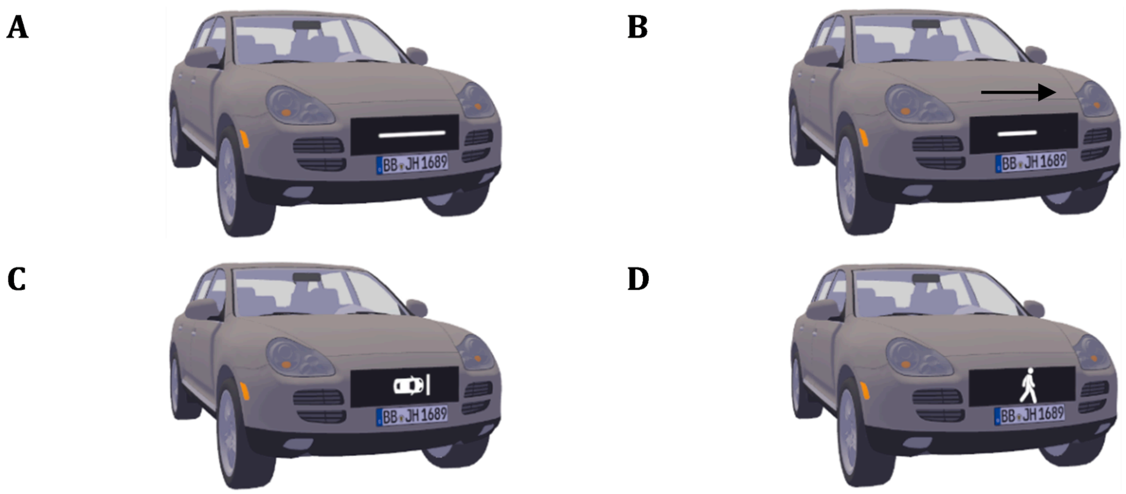

Fig. 3. The eHMI conditions. Panel A: Static light. Panel B: Dynamic light. Panel C: Static icon. Panel D: Dynamic icon.

(*very*). For improved immersion, the single-item scale was presented on virtual board on the opposite side of the road. Participants were instructed to give an answer by pressing one of five buttons with their index finger. After answering, the button lighted up providing instant visual feedback.

2.5.2. *Crossing behavior*

To deliver a holistic description of participant's crossing behavior, two behavioral measures were collected for each trial: (1) CIT and (2) mean walking speed. CIT was defined as difference between the time in seconds, at which the vehicle began to brake and the time the pedestrian began to move in crossing direction with one of the following body locations: head, upper arms, belly or ankles. A negative value indicated that participants initiate their crossing before the encountering vehicle started to brake. Mean walking speed represented the mean velocity in m/s of the participant during crossing, e.g. from the crossing initiation until reaching the opposite side of the 3.35-meter wide urban road. Both measures were included to assess traffic flow and road safety. A shorter CIT and a higher mean walking speed indicated a higher traffic flow. In contrast, in situations in which only some of the AVs were equipped with an eHMI, longer CIT and lower mean crossing speed for AV-encounters without eHMI might be seen as an indicator for road safety.

2.5.3. *User Experience Questionnaire – Short (UEQ-S)*

User experience regarding the presented eHMIs was assessed by the User Experience Questionnaire – Short (UEQ-S) developed by Schrepp et al. (2017). User experience is defined as "a user's perceptions and responses that result from the use [...] of a system, product or service" (International Organization of Standardization [ISO], 2019, p. 4). In the present context of AV to pedestrian communication, user experience means that the designed eHMI should provide information needed by the user to complete the crossing task. The UEQ-S entails eight semantic differentials arranged into two subscales: pragmatic and hedonic quality. Pragmatic quality aspects relate to the fulfillment of an individuaĺs goal while using a product. In contrast, hedonic quality aspects do refer to a product's potential for fun and pleasure (Diefenbach & Hassenzahl, 2011). In addition, an overall scale is reported. Participants evaluated semantic differentials using a seven-stage scale after the virtual reality experiment. Based on our data, the reliability of the subscales was acceptable with Cronbach's $\alpha = 0.86$ to 0.93 for pragmatic subscale and $\alpha = 0.80$ to 0.93 for hedonic subscale (George & Mallery, 2003).

2.5.4. *Igroup Presence Questionnaire (IPQ)*

To measure the participants' feeling of being and acting in a virtual environment, the German version of the Igroup Presence Questionnaire (IPQ; Schubert et al., 2001) was used. The questionnaire of Schubert et al. (2001) consists of 14 items which assess the dimensions spatial presence, involvement and experienced realism. Spatial presence relates to the feeling of being located in a virtual environment, involvement refers to attention processes and experienced realism addresses the comparability to reality (Schubert et al., 2001). Participants rated their level of agreement with each item on a Likert scale ranging from 0 to 6. Based on our data, the reliability of the subscales with Cronbach's $\alpha = 0.44$ to 0.71 was lower than that reported by Schubert et al. (2001; Cronbach's $\alpha = 0.68 – 0.80$).

2.5.5. *Additional measures*

In addition, several control measures were assessed by means of self-report questionnaires. Head-mounted displays can cause discomfort or even nausea (Kim, Park, Choi, & Choe, 2018). To ensure the discomfort did not influence the validity of the virtual reality experiment, participants specified their wellbeing during the experiment on the single-item Misery Scale (MISC; Bos et al., 2005) ranging from. 0 (*no problems*) to 10 (*vomiting*). Furthermore, participants were asked to indicate how long they have already had a valid driving license (0 – 4 years, 5 – 9 years, 10 – 14 years, 15 – 19 years, more than 20 years) and how many kilometers they have driven on average per year at day and at night (< 5000 km, 5000 – 10000 km, 10000 – 20000 km, more than 20000 km). Finally, we were interested in participants' experiences with computer games and virtual reality experiments in order to control their possible influence on the subjective feeling of safety while acting in a virtual environment. Therefore, participants rated how often they play computer games per week (0 – 2 days, 2 – 4 days, more than 4 days) and how frequently they have taken part in virtual reality experiments before (once, twice, three times, four times, more than four times).

2.6. *Data analysis*

2.6.1. *Data preparation*

Each participant completed 24 trials in total. Each participant experienced four trials in block A and 20 additional trials in block B. The total number of trials amounts to 1224. In trials, the motion of six body locations was tracked: the head, the right and the left upper arm, the belly and the right and the left ankle. The motion capturing system recorded participants' crossing in three dimensions, where the x-axis represents the forward movement, the y-axis the sideways movement and the z-axis the upwards movement. Since we were only interested in forward movement, only x-axis data were considered in the analysis. Before the analysis, the occurrence of early crossings was examined. Participants started to cross the road before the braking actions in ten out of 1224 trials, corresponding to nearly 0.01%.

Furthermore, motion data were checked for validity. Due to an error of the motion capturing system, motion data were completely missing for 12 trials. In further 15 trials, no forward movement (in x-axis direction) was recorded. These data files were excluded from the further analysis. After removing them, the total number of trials decreased to 1187.

In order to investigate the effect of eHMIs on traffic flow and road safety, we selected specific measurement intervals for each trial. Intervals for calculating CIT and mean walking speed ranged from the time, at which the vehicle began to brake, until the time, at which the pedestrians reached the sidewalk on the other side of the road. By exclusively analyzing motion data during the specific measurement interval, we emphasized pedestrains' reactions to approaching vehicles. To determine CIT, the histogram-based thresholding algorithm approach by Ismail and Marhaban (2009) was applied. Histogram-based thresholding is a commonly used method in image thresholding and segmentation. The approach intends to calculate the best pixel intensity threshold that differentiates the illustrated object from its background (Ismail & Marhaban, 2009). In the current study, the algorithm was used to determine the most suitable threshold to segment between standing still and moving forward. First, the time series of the x-coordinate of each body location was transformed to velocities. From every time series of velocity, a histogram function *h(x)* was formed using a kernel density estimation (Scott, 1992). Afterwards, all possible local peaks x_p and valleys x_v of the histogram function *h(x)* were determined. To protect the analysis from noise, only peaks and valleys whose density was more than 0.3 times of the density of the maximum peaks or the minimum valley were considered for the further analysis. The best threshold value x_{th} was selected among the values in x_v, whereby the very first and last valley of the histogram were not covered. The CIT was defined as the time when the velocity first exceeded the determined threshold value x_{th}. The single steps of the histogram-based thresholding approach are shown in Fig. 4.

In order to predict subjective safety feeling from crossing behavior using a functional linear model, a common time scale was required. The time scale of the recorded motion data varied depending on several circumstances, such as CIT. To eliminate such differences, the time interval [0,1] was chosen for the motion data, whereby the time values can be interpreted as percentage. While 0 represented the time at which the vehicle began to break, 1 represented the time at which the pedestrian reached the sidewalk on the other side of the road. A closer inspection of the motion data unveiled slight differences in the sampling rate due to the frame rate of the simulation. To combine all motion data into one data frame, further preprocessing was carried out. First, the raw data were merged by a common time interval from 0.04 to 1. Extra rows with missing values were added to the output if raw data had no matching time value. Therefore, missing values were replaced using a spline interpolation (Moritz & Bartz-Beielstein, 2017). In order to reduce the data size, the sampling interval was set to 0.05 and only these data points were used for the further analyses.

2.6.2. *Statistical analysis*

All analyses were done using the statistical software R (Version 3.5.0; R Core Team, 2018). To investigate the effect of eHMI on traffic flow and road safety, linear mixed modeling (LMM) was employed. LMM enables modeling of hierarchical structured data in which measurements are collected at different levels. This usually concerns individuals who are nested into groups, but also repeated measures in with measurements are nested within persons. In contrast to traditional regression analysis, LMM can correctly associate the subject with repeated measures. It incorporated the data collected at different levels into one model, while yielding reasonably regression estimates for each level (Nezlek, 2008). In the analyses, CIT, mean walking speed and subjective safety feeling served as dependent variables. For CIT and mean walking speed, three-level models with participants as level-3-variable, body part as level-2-variable and experimental trial as level-1-variable were created. For subjective safety feeling, we constructed two-level models with participants as level-2- and experimental trial as level-1-variables. Model testing proceeded in several steps. First, a null model was computed to test to what extent participants differ in terms of dependent variables (Luhmann, 2015). Intercepts were allowed to vary randomly across participants. Based on the null model the intra-class correlation (ICC) was calculated. A high ICC means that that there is relatively high variance between participants (Nezlek, 2008). We reported ICC as standardized effect size measure for participants (level 2), as recommended by Lorah (2018). It can be interpreted as the correlation coefficient. To investigate the effect of eHMI and scenario on traffic flow, the variables were introduced as independent variables at level 1. To rule out biases due to the incomplete measure design, only data of block B were considered in these analyses. To explore the effect of eHMI on road safety, further LMMs

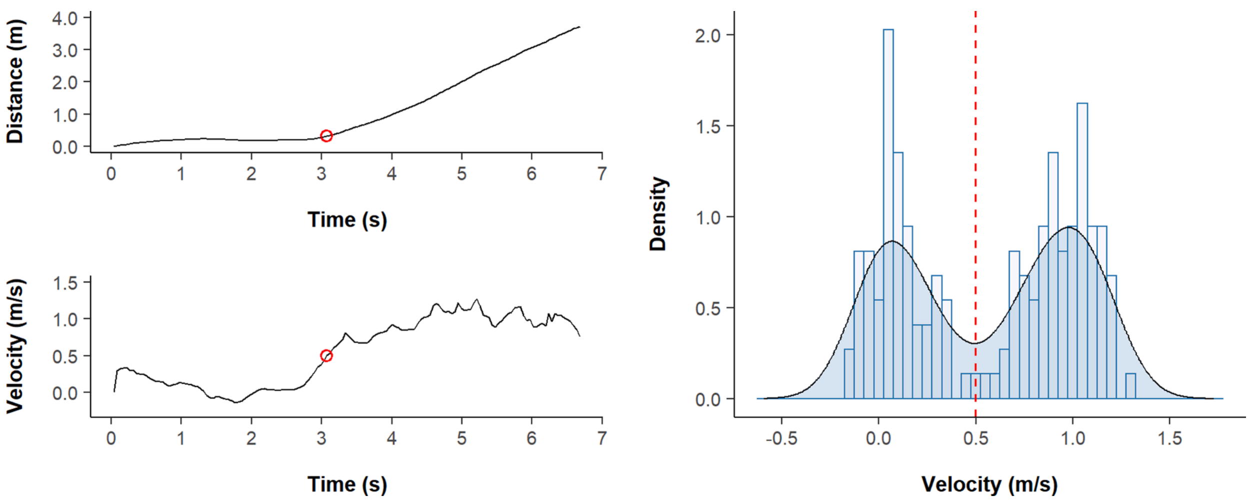

Fig. 4. An example for the automatic detection of CIT for each body location. The left panels show the forward movement (in x-axis direction) and the velocity according to time. The right panel shows the histogram function h(x) of velocity. Red points and dashed line indicate the best threshold value x_{th}. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Descriptive statistics for CIT, mean walking speed and subjective safety feeling.

Measure	Block A		Block B									
	No eHMI		No eHMI		Static light		Dynamic light		Static icon		Dynamic icon	
	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night	Day	Night
CIT [s]												
M	3.48	3.49	3.56	3.71	3.07	3.21	2.96	2.99	3.12	3.17	2.72	2.85
SD	1.12	0.98	0.82	0.78	0.93	1.02	0.87	0.90	0.94	0.95	0.92	0.95
Mean walking speed [m/s^2]												
M	1.02	1.03	1.05	1.03	1.04	1.05	1.04	1.04	1.04	1.03	1.05	1.06
SD	0.14	0.14	0.13	0.13	0.14	0.14	0.13	0.14	0.14	0.15	0.12	0.14
Subjective safety feeling												
M	4.26	4.08	3.73	3.49	3.92	3.92	4.29	4.36	4.08	3.98	4.74	4.60
SD	0.66	0.75	0.83	0.92	0.82	0.76	0.69	0.56	0.83	0.82	0.43	0.49

were conducted. Specifically, we investigated if participant's reactions for encounters without eHMI differ between block A and block B. Accordingly, block was investigated as dummy-coded independent variable on level 1. We used the standardized regression coefficient as standardized effect size measure for level-1 predictors (Lorah, 2018). Power of LMM models mainly depends on sample size on the highest level (Maas & Hox, 2005). According to a simulation study by Maas and Hox (2005), our final sample size of $N = 51$ seemed sufficient for an accurate estimation of regression coefficients.

A functional linear model was used to examine the association between subjective safety feeling and crossing behavior. The application of functional data analysis became more common in the analysis of activity and movement patterns in children and adolescents (Ramsay, Hooker, & Graves, 2009; Xiao et al., 2015). The approach models densely sampled measures, rather than reducing single data points (Ramsay et al., 2009). Our study collected motion data for each participant on multiple trials. To account for the hierarchical structure of the data in which trials were nested within participants, multilevel functional mixed models were computed for each body location. To avoid bias due to the incomplete repeated measures design, only data from block B were considered. In order to handle the high frequency time-series data, we performed principal component analysis (PCA) to reduce dimensions. Precisely, the two-level functional principal component analysis model proposed by Di, Crainiceanu, Caffo, and Punjabi (2009) was used. Afterwards, the subjective safety feeling was regressed on the principal component scores. With regard to functional data analysis, no a priori power analysis was conducted due to this type of analysis being exploratory in nature.

CIT, mean walking speed and subjective safety feeling were analyzed in terms of homogeneity of variances and normal distribution. For all variables, the two assumptions were violated. To fulfill the criterion of normality, the variables were transformed using a Yeo-Johnson Transformation (Yeo, 2000). As the LMM results for the non-transformed variables did not differ from those for the transformed, the conducted statistical analysis proved to be robust against the violation of the normality assumption. As non-transformed variables are easier to interpret, results of LMMs for non-transformed variables are reported.

3. Results

3.1. Descriptive statistics

Table 1 shows descriptive statistics for CIT, mean walking speed and subjective safety feeling by experimental block, eHMI and scenario. We descriptively analyzed if there were differences between the times at which each body part began to move forward. It was found that the forward movement of the body part can be divided into two steps (see Fig. 5). First, the left upper arm ($M = 2.90$, $SD = 0.82$), the head ($M = 2.94$, $SD = 0.81$), the right upper arm ($M = 2.97$, $SD = 0.83$) and belly ($M = 2.98$, $SD = 0.81$) started to move forward. Subsequently, the left ($M = 3.64$, $SD = 0.82$) and the right ankle ($M = 3.64$, $SD = 0.82$) began their movement in forward direction. No significant differences were found between head, belly and upper arms regarding CIT. For further analysis, LMM were used due to the hierarchical data structure.

3.2. Crossing behavior

Regarding LMMs, all null models were significant with $p < .001$. Thus, participants significantly differed in their CIT and mean walking speed. The ICC for CIT was 0.63 and 0.74 for mean walking speed indicating high individual differences. To investigate their effect on traffic flow, eHMI and scenario were used as independent variables at level 1. Since the LMMs with interaction term provided a better fit to the data, the results of LMMs considering interactions are reported. The results are displayed in Table 2. A significant effect for eHMI was found, indicating a lower overall CIT while approaching an AV with eHMI compared to encounters without eHMI. In general, participants showed significantly decreased CITs for the static light, dynamic light, static icon and dynamic icon eHMI condition compared to not having an eHMI present. In addition, the main effect of scenario was significant at the specified $p < .05$ level, showing higher CIT by night than by day. Besides main effects, the dynamic light and static icon eHMI condition significantly

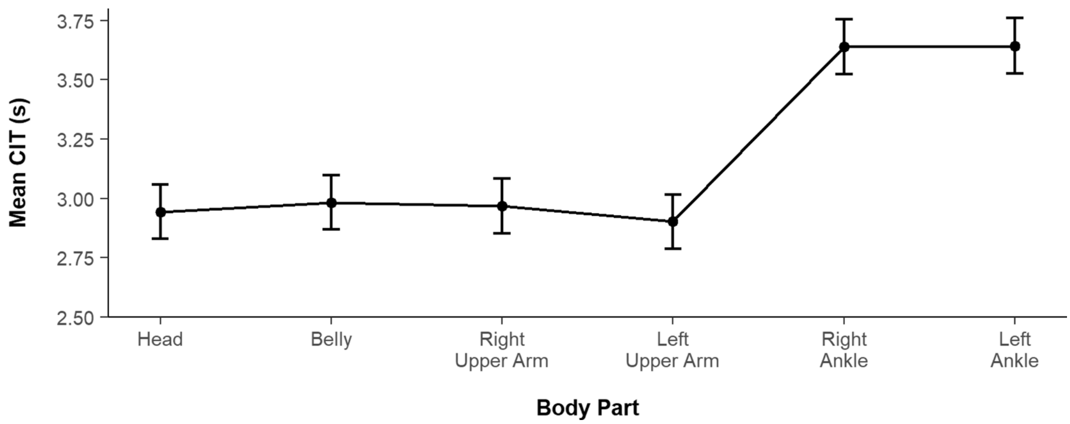

Fig. 5. Mean value of CIT for each body part. Error bars represent standard error.

Table 2
Linear Mixed Models for CIT, mean walking speed and subjective safety feeling.

	CIT				Mean walking speed				Subjective safety feeling			
Variables	β	*SE*	*t*	*p*	β	*SE*	*t*	*p*	β	*SE*	*t*	*p*
Level 1 main effects												
eHMI[a]												
Static light	−0.43	0.03	−13.52	<0.001	−0.03	0.03	−1.11	0.269	0.22	0.04	5.44	<0.001
Dynamic light	−0.53	0.03	−16.60	<0.001	−0.02	0.03	−0.72	0.473	0.66	0.04	16.22	<0.001
Static icon	−0.39	0.03	−12.20	<0.001	−0.03	0.03	−1.01	0.313	0.40	0.04	9.99	<0.001
Dynamic icon	−0.74	0.03	−23.25	<0.001	0.02	0.03	0.54	0.587	1.17	0.03	28.97	<0.001
Scenario[b]	0.14	0.03	4.39	<0.001	−0.11	0.03	−3.77	<0.001	−0.27	0.04	−6.50	<0.001
Level 1 interactions												
Scenario[b] * Static light	−0.02	0.05	−0.42	0.671	0.15	0.04	3.55	<0.001	0.29	0.06	5.02	<0.001
Scenario[b] * Dynamic light	−0.14	0.05	−3.00	0.003	0.11	0.04	2.57	0.010	0.35	0.06	6.13	<0.001
Scenario[b] * Static icon	−0.10	0.05	−2.34	0.025	0.05	0.04	1.11	0.269	0.15	0.06	2.62	0.009
Scenario[b] * Dynamic icon	−0.05	0.05	−1.02	0.308	0.15	0.04	3.48	<0.001	0.12	0.06	2.10	0.035

Note. Standardized regression coefficients are given.
CIT is sampled in s, mean walking speed in m/s^2.
[a] Reference category is categorical variable no eHMI.
[b] 0 = daytime scenario and 1 = nighttime scenario.

interacted with scenario. The coefficients were negative, which implies that the effect of scenario on CIT is lower for these eHMI conditions. Post-hoc multiple comparisons using Turkey HSD test with Holm correction revealed significant differences between the eHMIs at $p < .05$, except for a difference between static light and static icon. When looking on mean walking speed, no significant association with eHMI was found, all $ps > 0.05$. However, there was a significant, small effect of $\beta = -0.11$ for scenario ($t(5640.31) = -3.77$, $p < .001$), showing that pedestrians' mean walking speed was slightly lower at night than at day. In addition, the eHMIs static light, dynamic light and static icon interacted with scenario. Thus, the effect of scenario varied between eHMIs.

To investigate whether eHMI can contribute to improved road safety, further LMMs were conducted. In the analyses, the block was investigated as a dummy-coded independent level-1-variable. Regarding CIT, the results indicated a significant main effect for block ($\beta = 0.13$, $t(1994.57) = 4.82$, $p < .001$). Regarding mean walking speed, the LMM revealed a significant main effect of $\beta = 0.07$ for the block ($t(1992.78) = 2.81$, $p = .005$). Thus, in block B in which only some encountering AVs displayed an eHMI, participants showed an increased CIT and a decreased mean walking speed compared to block A. Therefore, participants tended to become more uncertain and conservative for breaking actions in which an eHMI was absent.

3.3. Subjective safety feeling

In accordance to objective measures, the null model of subjective safety feeling was significant. The ICC of 0.34 indicated high individual differences between participants. Regarding traffic flow, the LMM revealed significant main effects for eHMI and scenario as well as significant interactions between eHMI and scenario. Participants felt significantly safer when crossing in front of an AV equipped with an eHMI compared to crossing in front of an AV without an eHMI. Furthermore, subjective safety rating was

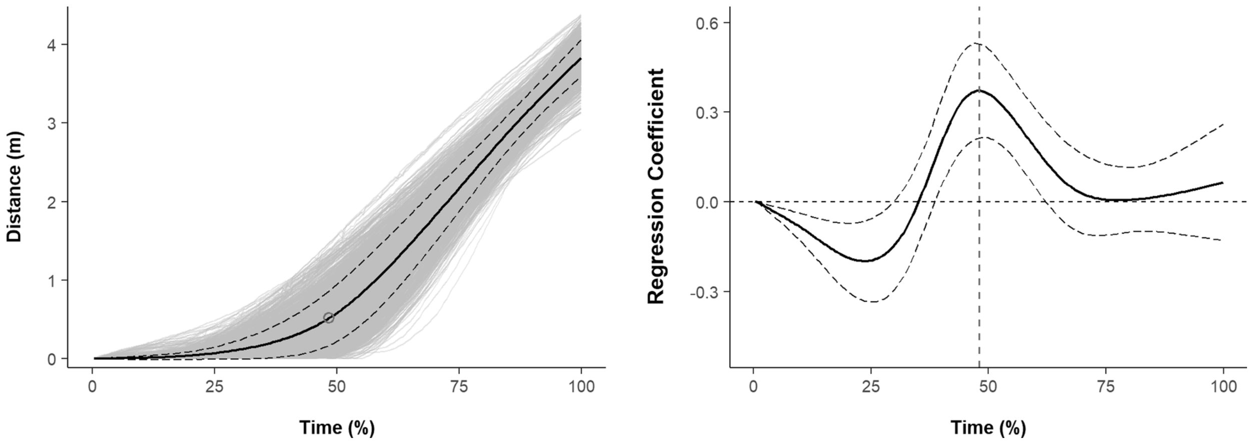

Fig. 6. Left panel: Observations of the head movement in x-direction. Gray: Single observations for each trial. Black: Mean function with added standard deviation functions. Right panel: Estimated β(t) for predicting subjective safety feeling from head motion in x-direction. The dashed lines show pointwise 95% confidence intervals for values of β(t). Red point and dashed line indicate the CIT for the mean function. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

significantly lower during the night than during the day (β = −0.27, $t(5893.49) = -6.50$, $p < .001$). A post-hoc test with holm correction revealed that there are significant differences between eHMI concepts, all $ps < 0.001$. To investigate the effect of eHMI on road safety, we compared subjective safety feeling during AV encounters without eHMI between block A and block B. The LMM showed a significant main effect for block (β = -0.62, $t(2246.14) = -23.35$, $p < .001$), indicating a lower subjective safety feeling for braking actions in block B compared to block A.

3.4. Predicting subjective safety feeling from crossing behavior

In order to investigate if subjective safety rating can be reliably predicted from objective crossing behavior, a functional data analysis was conducted separately for each body part. Since each analysis came to the same conclusion, only the results concerning head motions are presented. Results for all body parts can be found in supplemental material. A functional linear model with subjective safety feeling as dependent variable and functional motion data as independent variables was fitted according to the data. First, a two-level principal components model was carried out to discover the source of variance. The left panel of Fig. 6 illustrates head motion data in x-direction for all trials and participants. The sampled curves are displayed with thinner lines, whereas mean function is plotted with a thick line. The PCA revealed three functional principal component scores for level 2 and four functional principal component scores for level 1. While level 2 accounts for 54.3% of the total variance, level 1 explained 45.7%. The large amount of explained variance on level 2 indicates that participants differ considerably in their crossing behavior. The first level 1 principal component eigenfunction described 39.8%, the second 4.1%, and the third and the fourth component 1.5% and 0.4% of the total variance in crossing behavior.

Table 3 shows the results of the linear multiple regression model examining the association between subjective safety feeling and crossing behavior. Results indicated that crossing behavior predicted subjective safety feeling, $R^2 = 0.03$, $F(4,994) = 8.04$, $p < .001$. In the model, level 1 principal component 1 (β = −0.10, $t(994) = -3.21$, $p < .01$) and principal component 4 (β = 0.12, $t(994) = 3.85$, $p < .001$) were significant predictors. However, the predictors explained only 3% of the variance. The right panel of Fig. 6 shows the estimated regression coefficient function β(t) for predicting subjective safety feeling from crossing behavior. The figure indicates that only the first part (up to 50%) of the time scale really matters in defining the association between subjective safety feeling and crossing behavior and the slight oscillations over the second part of the time scale are coincidental. Indeed, the time point of the highest regression coefficient $\beta_{max}(0.47) = 0.37$ was equivalent to the CIT of the mean function determined on the basis of the histogram-based thresholding algorithm.

3.5. User experience

Descriptive statistics for the pragmatic quality scale, the hedonic quality scale and the overall user experience can be found in Table 4. According to the guidelines of Hinderks, Schrepp, and Thomaschewski (2019), overall user experience scores can be interpreted as negative for the static light eHMI ($M = -1.15$, $SD = 0.89$) and neutral for the dynamic light ($M = -0.08$, $SD = 1.10$) and the static icon eHMI ($M = -0.43$, $SD = 1.11$). Only the dynamic icon eHMI ($M = 0.88$, $SD = 0.83$) showed positive evaluation with an overall scale value over 0.8.

3.6. Presence Questionnaire and MISC scale

The Presence Questionnaire indicated high immersion and ecological validity. General presence was rated high ($M = 4.54$, $SD = 1.39$). Furthermore, the descriptive statistics of the MISC scale ($M = 0.38$, $SD = 1.23$) suggested that discomfort was very low during the virtual reality experiment. 43 out of 51 participants reported no symptoms, three participants slight symptoms and two participants little nausea.

4. Discussion

The current study proposes a motion-based approach for virtual reality experiments to investigate the effect of eHMIs on traffic flow and road safety. The validation of the approach followed a two-step procedure: First, we explored how eHMIs affect subjective safety rating and true to life crossing behavior, measured using CIT and mean walking speed. To increase the generalizability of the findings, two scenarios were investigated. Second, we predict subjective safety-ratings by actual crossing behavior. Altogether, findings indicate

Table 3
Linear regression of subjective safety feeling on level-1 PC scores of head movement in x-direction.

Variable	*B*	95% CI for *B*	β	*t*	*p*
Constant	4.11	[4.06, 4.16]	0.00	151.72	<0.001
PC1	−0.40	[4.06, 4.16]	−0.10	−3.21	0.001
PC2	0.46	[-0.65, −0.16]	0.03	0.91	0.363
PC3	−0.06	[-0.53, 1.45]	0.00	−0.07	0.943
PC4	5.93	[-1.66, 1.53]	0.12	3.85	<0.001

Note. CI = confidence interval. PC = Principal component.

Table 4
Descriptive statistics for UEQ-S.

Measure	Static icon		Dynamic icon		Static light		Dynamic light	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Pragmatic quality	−0.37	1.49	1.64	0.66	−0.52	1.36	0.27	1.43
Hedonistic quality	−0.50	1.17	0.12	1.27	−1.77	0.88	−0.42	1.29
Overall	−0.43	1.11	0.88	0.82	−1.15	0.89	−0.08	1.10

that CIT is an appropriate and sensitive measure for assessing traffic flow and road safety. Results showed decreased CITs and higher subjective safety feeling for AV-encounters with eHMI compared to having no eHMI present. However, there was no significant effect for mean walking speed. Participants reported to feel significantly safer and crossed earlier when an eHMI was displayed compared to no eHMI. Furthermore, subjective safety rating could be predicted from actual crossing behavior above chance suggesting a high ecological validity of the approach. The results will be discussed in the following section.

4.1. Effect on crossing behavior

Extending previous studies (e.g., Chang et al., 2017), we investigated pedestrains' actual crossing behavior while encountering an AV. The present study found evidence that eHMIs have a significant effect on CIT. Pedestrians crossed the road earlier when encountering an AV with an eHMI compared to no eHMI. In contrast to previous results, CIT significantly differed between the presented eHMIs. Recent studies operationalized CIT in a completely different form. For example, Othersen et al. (2019) defined the crossing initiation as the point when participants' head moved 70 cm in crossing direction. While the results showed significant effects of eHMI on CIT, no differences between the eHMIs were observed. In contrast, our motion-based approach does not provide an approximation of CIT, but a reliable measurement via histogram-based thresholding. Therefore, the different results are probably due to the anticipated sensitivity of the methodological approaches. Moreover, analysis revealed a significant effect of scenario on CIT. In line with Beggiato, Witzlack, and Krems (2017), a decreased visual acuity at night increased pedestrians' CIT.

In contrast to CIT, mean walking time was not significantly influenced by the application of an eHMI. This result supports the conclusion of Deb, Strawderman, and Carruth (2018) that only audible signals influence crossing time. The authors suggest that an audible signal can be perceived as an alarm signal instead of an information and can confuse pedestrians to such an extent that they do not cross. There was a significant effect for scenario on mean walking time. However, the effect size was small: Pedestrians crossed the road slightly faster by night than by day.

In addition to traffic flow, we were interested in the effect of eHMI on road safety. The results of the study revealed that in a mixed traffic environment, in which only a portion of the vehicles were equipped with an eHMI, pedestrians crossing behavior became more conservative for AVs in which an eHMI was absent. In block B, in which only a portion of AVs was equipped with an eHMI, participants crossed the road later and faster when encountering an AV without an eHMI compared to block A. This is in line with the study of Petzold et al (2016), in which more conservative reaction times were found for braking actions without eHMI. The authors concluded that this conservative behavior could be an indicator for a beneficial effect of eHMIs on road safety. In situation in which only some of the braking actions was accompanied by an eHMI, pedestrians wanted to be sure that AVs without eHMI were actually braking. Therefore, a positive effect of eHMI on road safety can be assumed.

4.2. Effect on subjective safety feeling

Besides the effect of eHMIs on crossing behavior, we were interested in their effect on subjective safety rating. In line with previous research (de Clercq et al., 2019; Faas et al., 2020; Langström et al., 2015), the findings of the study revealed that pedestrians felt safer to cross when encountering an AV with an eHMI compared to encounters without eHMI. According to Malmsten Lundgren, Habibovic, Andersson, Lagström, Nilsson et al. (2017), eHMIs help to meet pedestrians' new communication needs that arise from increasing levels of vehicle automation. In addition, subjective safety ratings were higher for dynamic eHMIs, namely the walking man animation and the dynamic light, compared to the static ones. This is consistent with the previous results, according to which dynamic displays are clearly perceptible, whereas static displays were not (Othersen et al., 2019). The walking man animation is a very common feature at pedestrian crossings and thus provided the pedestrians with something they were comfortable with, as a signal of vehicles intention to let them cross. It indicates to pedestrians that it is safe to cross the road. However, providing guidance information can result in additional risks if AVs do not account for surrounding traffic (ISO, 2018). Since the effect of eHMIs might be confounded with their presented message, these results should not be over-interpreted. Furthermore, the current study adds evidence that the subjective safety ratings differed between the scenarios, whereby participants reported to feel safer while crossing during the day than during the night. As already mentioned in the section above, the subjective safety feeling might be due to low visual acuity at night (Ackermann et al., 2019). More importantly, in situations in which only some of the AVs were equipped with an eHMI, pedestrians reported to feel more insecure while crossing when encountering an AV without an eHMI compared to encounters with eHMI. Thus, the present study adds evidence to previous studies (Petzold et al., 2017), showing that eHMIs contribute to enhanced road safety in a mixed traffic environment. In summary, the methodological approach was able to detect comparable effects of eHMI on both crossing behavior and subjective safety feeling. In contrast to previous studies, the UEQ-S revealed a negative evaluation of the general application of eHMIs. None of the eHMI was positively evaluated, except for the dynamic icon eHMI. Recent studies used other eHMI designs (Faas et al.,

2020) and presented the eHMIs in a blue-green color. The use of this color is recommended by SAE International (2019) for automated driving system lamps. In our study, eHMIs were presented in white color on a black display for best contrast performance, especially for icon-based designs. Although clearly visible in principal, the color is not novel in traffic and might therefore not appear suitable for AVs. Furthermore, in previous studies the meaning of eHMIs was explained to the participants before the experiment, which might have distorted their evaluation (Faas et al., 2020).

4.3. Predicting subjective safety feeling from crossing behavior

In the existing literature, no attempts have been made to validate objective measures by considering subjective and objective measures. We validated the proposed approach by predicting subjective safety feeling by actual crossing behavior with a functional data analysis approach. The results of the present study suggest that subjective safety feeling can be significantly predicted from objective crossing behavior. The association was highest at the CIT of the mean function, indicating the ecological validity of the measure. However, the explained variance was relatively low. This may be due to high interindividual differences in crossing behavior and subjective safety rating. The functional data analysis revealed that differences in crossing behavior are mainly due to personal differences. This result supports the assumption of Clamann (2017) that pedestrians use individual crossing strategies. Beside individual differences, eHMI and scenario are main factors influencing pedestrians' subjective safety feeling while interacting with an AV.

5. Limitations and future research

The present study was conducted in virtual reality using a head mounted display. Using virtual reality, new types of feedback can be examined in a safe and controlled manner. The presence questionnaire indicated that participants had the impression of being and acting in the virtual environment. This indicates that virtual reality experiments may be an adequate alternative for field experiments. However, in the context of an empirical study, a functional prototype of an eHMI should of course also be evaluated under real world traffic conditions in order to validate the research findings in a real-life setting. A major limitation of the present study was the artificial and predictable experimental setup. In particular, participants stood on a defined starting point in front of a non-signalized intersection and vehicles approached from the left side. All vehicles showed the identical deceleration strategy. In order to reduce any distraction and enable participants to concentrate on the eHMIs of the approaching vehicles, neither oncoming traffic nor other pedestrians were incorporated in the virtual reality environment. While the experimental setup allowed for controlled and replicable testing conditions, it did not reflect real-life daily traffic scenarios. Future studies should include manually operated vehicles, encountering AVs from multiple directions and additional pedestrians. Furthermore, more ambiguous traffic scenarios requiring vehicle–pedestrian-communication should be considered in order to maximize the environmental generalizability of the research findings.

A further limitation goes back to the fact that participants were informed about the existence of the display on the radiator grille, since we assumed that participants could be confused about the display. This information might have primed and biased participants into paying attention to the indicators on the display. Furthermore, the effect of eHMIs might be confounded with their presented message. While static displays primarily signalized the vehicle's intention to stop, dynamic displays explicitly provided the advice to cross. The present study focused on the validation of appropriate behavioral measures for evaluating eHMIs, not on the concept and the design of the eHMI. Ideation workshops and further experimental studies should target what message should be displayed and how this message can be presented in an intuitively understandable and perceivable design. Apart from eHMI, it should be considered that vehicle speed and deceleration can be used for informal communication with pedestrians (Beggiato et al., 2017).

Finally, the sample of the present study cannot be considered as representative for the general population. Participants with a technical profession were overrepresented in our sample what may lead to a higher affinity towards prospective technologies. Future studies should address more vulnerable road users such as children and elderly pedestrians in order to develop eHMI concepts which are suitable and understandable for different age groups. Moreover, the study was conducted in Germany with a western culture, where the general traffic and pedestrian behavior are strictly regulated by legal rules (Färber, 2016). In other cultures (e.g., Asia), road user behavior, infrastructure support and legal regulations differ basically from Europe or North America (Rasouli & Tsotsos, 2019). Thus, it seems appropriate to investigate cross-cultural differences in the interaction between AVs and pedestrians. Furthermore, the feasibility of eHMIs across different cultures should be examined to develop cross-culturally appropriate eHMI solutions.

6. Implications and conclusion

The study gave further insights into the road crossing behavior of pedestrians in response to communication via eHMIs. The results of the present study showed that the general use of eHMIs contribute to an optimized traffic flow and a higher road safety. Participants crossed the road significantly earlier when encountering AVs with eHMI. In addition, when only some of the braking actions were accompanied by eHMI, participants' crossing behavior became more conservative for braking actions in which an eHMI was absent. This conservative crossing behavior can be seen as an indicator for the positive effect of eHMIs on road safety (Petzold et al., 2017). Regarding subjective feelings, the study provides evidence that pedestrians feel more secure when crossing if the AV is equipped with an eHMI. Hence, it seems recommendable to provide eHMIs in order to enhance traffic flow, road safety and subjective safety feeling while encountering an AV.

Besides these practical implications, the results demonstrated that the proposed motion-based approach provide new possibilities to evaluate eHMI concepts. In previous literature, eHMI concepts were mainly evaluated using self-reports. Yet, self-reports are based on introspection and therefore susceptible to subjective bias such as response tendencies. In contrast, behavioral measures are less likely to deliberately controlled and are a more objective measure than self-reports (Rietveld, 2008). While subjective measures are used to assess behavior retrospectively, objective measures are suitable to assess moment-to-moment changes in behavior. The present study showed that subjective safety feeling can be reliably predicted by motion sensing data while crossing the road. Therefore, crossing behavior of pedestrians encountering an AV represent are valid measure which can increase the ecological validity of experiments investigating vehicle–pedestrian interaction. In conclusion, we argue that using behavioral measures has some great potential. By analyzing crossing behavior, it can be investigated how new means of communication between AVs and pedestrians affect traffic flow and road safety.

CRediT authorship contribution statement

Janina Bindschädel: Conceptualization, Methodology, Software, Formal analysis, Investigation, Resources, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Ingo Krems:** Software, Writing – original draft. **Andrea Kiesel:** Conceptualization, Writing – original draft.

Declaration of Competing Interest

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

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trf.2021.08.018.

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