Pedestrian Crossing Decisions in Virtual Environments: Behavioral Validity in CAVEs and Head-Mounted Displays

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Objective: To contribute to the validation of virtual reality (VR) as a tool for analyzing pedestrian behavior, we compared two types of high-fidelity pedestrian simulators to a test track.

Background: While VR has become a popular tool in pedestrian research, it is uncertain to what extent simulator studies evoke the same behavior as nonvirtual environments.

Method: An identical experimental procedure was replicated in a CAVE automatic virtual environment (CAVE), a head-mounted display (HMD), and on a test track. In each group, 30 participants were instructed to step forward whenever they felt the gap between two approaching vehicles was adequate for crossing.

Results: Our analyses revealed distinct effects for the three environments. Overall acceptance was highest on the test track. In both simulators, crossings were initiated later, but a relationship between gap size and crossing initiation was apparent only in the CAVE. In contrast to the test track, vehicle speed significantly affected acceptance rates and safety margins in both simulators.

Conclusion: For a common decision task, the results obtained in virtual environments deviate from those in a nonvirtual test bed. The consistency of differences indicates that restrictions apply when predicting real-world behavior based on VR studies. In particular, the higher susceptibility to speed effects warrants further investigation, since it implies that differences in perceptual processing alter experimental outcomes.

Application: Our observations should inform the conclusions drawn from future research in pedestrian simulators, for example by accounting for a higher sensitivity to speed variations and a greater uncertainty associated with crossing decisions.

Keywords: pedestrians, virtual environments, behavioral validity, CAVE, HMD

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Presenting humans with virtual traffic allows researchers to analyze pedestrian behavior in a risk-free, controllable, and flexible environment. Particularly when investigating vulnerable populations and novel technologies, virtual reality (VR) is considered a safe and cost-efficient alternative to test tracks and physical prototypes (Schneider & Bengler, 2020). There is, however, little empirical evidence to demonstrate that pedestrian simulators constitute an adequate replacement for nonvirtual test beds, and research on the nature of possible deviations from real-world behavior is limited.

The concept of validity refers to the congruence between an experimental setup and the real-world entity it shall reflect. Behavioral validity, pertaining to the agreement of human behavior, is particularly relevant when experimental outcomes influence real-world decisions (Mullen et al., 2011). Despite a number of related studies in driving simulation, the extent of behavioral validity and its dependence on the congruence of physical stimuli are yet unclear (Wynne et al., 2019). For pedestrian simulators, for which thorough validation studies are scarce (Schneider & Bengler, 2020), generalizing results to real-world traffic seems even more tentative. Since a number of restrictions apply to virtual environments, including biases in risk and distance perception (Rasouli & Tsotsos, 2019; Renner et al., 2013), systematic comparisons are required to assess the generalizability of experimental findings.

Pedestrian Behavior in Virtual and Nonvirtual Environments

Human behavior in virtual environments is affected by features of the interface, the model environment, and how they support task performance. The well-documented phenomenon of distance compression, for example, is not limited to specific hardware (Renner et al., 2013), but may be exacerbated by a restricted field of view (FOV) and the weight or inertia of head-mounted displays (HMDs). Similarly, biases in speed perception and affordance judgments can depend on the presence of haptic feedback and a self-avatar, contextual features, and the quality of visual representation (Feldstein, 2019; Lin et al., 2015).

Considering the diversity of potential influences, VR-related biases should be examined specifically in the context of modern pedestrian simulators. Walking through an urban street environment, pedestrians in VR exhibited longer fixations, shorter saccades, and a stronger visual focus on the center of the scene (Berton et al., 2020). They walked more slowly and increased lateral distances, possibly due to the awareness for physical boundaries, the lack of an ego representation, and a limited FOV (Iryo-Asano et al., 2018). For pedestrian street crossing, Schwebel et al. (2008) found moderate correlations between crossing decisions in VR and on-road traffic for both children and adults. A subsequent analysis of the adults' data revealed significant offsets in start delay, the average size of accepted gaps, and safety margins (Feldstein, 2019).

In comparison to on-road traffic, protected physical environments like test tracks allow to investigate technologies that are not yet available on public roads and to clarify the impact of technical interfaces thanks to enhanced experimental control. Again, VR-related changes in pedestrian behavior have been reported: In contrast to a physical street, crossing decisions in VR appear to depend on spatial rather than temporal distance, leading to reduced safety margins (Feldstein & Dyszak, 2020). Vehicles approaching at 90° seemed more dangerous in VR, possibly due to their "sudden" appearance in a restricted FOV (Iryo-Asano et al., 2018). Vehicle speed in VR was perceived as higher and presence was lower than on a test track, and crossing intention dropped from 26.5% to 13.9% in an experiment by Bhagavathula et al. (2018). In the same study, distances were underestimated to a similar extent in both environments, supporting the idea that recent HMDs mitigate distance compression (Kelly et al., 2017). Sounds emitted by electric vehicles were detected later and considered less recognizable in VR, although pleasantness rankings were equal to a physical street (Singh et al., 2015).

Comparison of Simulator Types

While generally suggesting a bias when investigating pedestrian behavior in VR, previous comparisons to nonvirtual environments depend on the respective hardware. In recent years, CAVE automatic virtual environments (CAVEs) and HMDs have emerged as two types of immersive pedestrian simulators (Schneider & Bengler, 2020). CAVE-like systems consist of multiple, large, static screens or projections, usually allowing participants to walk between them while adjusting the visual perspective to their point of view. In HMDs, in contrast, the display moves with the participant. Despite considerable variance within these categories, both are linked to certain characteristics such as limitations in FOV or field of regard, the availability of stereovision, the presentation of auditory cues, the visibility of the participant's body and their physical surroundings, and restrictions imposed by obstacles or the range of the tracking equipment (Cordeil et al., 2017; Juan & Pérez, 2009; Mestre, 2017).

Again, comparisons between simulator types are affected by hardware and task requirements. In driving simulation, for instance, CAVEs and HMDs provoked similar performance and physiological outcomes, but simulation sickness seemed more pronounced in the HMD (Weidner et al., 2017). Borrego et al. (2016) observed equally low sickness for an HMD that allowed naturalistic walking and a CAVE in which movement was controlled by a joystick, but the HMD elicited higher presence ratings. For an HMD with a small FOV, which prevented naturalistic walking, in contrast, presence and anxiety reactions were weaker than in a CAVE (Juan & Pérez, 2009). Distance perception did not vary significantly between the two devices (Ghinea et al., 2018; Grechkin et al., 2010).

Regarding street crossing, Mallaro et al. (2017) found that participants wearing an HMD accepted smaller gaps, whereas those in a CAVE discriminated more clearly between gap sizes. While the latter also stood closer to the road, crossing initiation was timed more precisely in the HMD. A within-subject study based on the same technology as the present work confirmed higher acceptance rates and earlier crossings in the HMD, but the effect size depended on age (Cavallo, Dang, et al., 2019). Contrasting the results of Mallaro et al. (2017), the HMD led to slower crossings and more collisions for 11- to 12-year-olds, whereas no such effect was observed for adults. For a train-boarding task imposing demands comparable to street crossing, Grechkin et al. (2014) observed similar acceptance probabilities in CAVEs and HMDs. With the HMD, however, participants started later, walked faster, and experienced more boarding failures. Again, results may have been affected by the HMD's small FOV, which does not correspond to current standards.

Objective of the Present Study

Despite the popularity of pedestrian simulators, behavioral outcomes in VR can be expected to deviate from nonvirtual environments. To our knowledge, only two studies analyzed effects on crossing decisions in HMDs, both displaying but a single vehicle. Findings are inconsistent, with Feldstein and Dyszak (2020) reporting that smaller and thus more gaps were accepted in VR, whereas crossing intent decreased in Bhagavathula et al. (2018). No similar study exists in respect to CAVE-like simulators. Since street crossing represents a frequent use case (Schneider & Bengler, 2020), additional research is needed to clarify potential biases. This is particularly true since the influence of naturalistic walking and the quality of visual representation question the applicability of earlier findings. As observations may be specific to either CAVEs or HMDs (Cavallo, Dang, et al., 2019; Mallaro et al., 2017), we aimed to provide a systematic comparison between a test track and both types of high-fidelity pedestrian simulators.

METHOD

Experimental Design

To limit carry-over effects, the three environments were presented to independent groups. In each trial, two cars approached from the right, and participants were instructed to step forward if the temporal gap between them seemed sufficient to cross the street safely. Cars maintained a speed of either 30 or 50 km/hr, forming gaps of 1, 2, 3, 4, or 5 s. Each speed-gap combination was presented twice per participant, resulting in a total of 20 experimental trials, whose order was randomized. Dependent measures included

a. Acceptance or rejection of a gap.
b. Crossing initiation time (CIT): time between the moment when the rear of the first vehicle had passed and the moment when the participant started crossing (Figure 1).
c. Postencroachment time (PET): temporal margin between the hypothetical moment when a pedestrian would leave the middle part of the street (based on pre-experimental measurements of walking speed) and the moment when the front of the second car reached their crossing line (Figure 1).
d. Self-reports of perceived risk, realism, and the agreement with real-world behavior.

Apparatus and Scenario

The experimental environment comprised a parking lot on the campus of the Technical University of Munich at Garching, featuring a single straight lane of 4.8 m width and 450 m length. Cars started accelerating at a distance of 320 m from the observer. Participants were instructed to step forward at the moment they would initiate crossing (Figure 2), thereby triggering a SMARTSPEED timing gate system located in front of them. Additional gates along the street allowed us to record this movement relative to the position of the approaching vehicles. With the exception of the test vehicles, parking and driving on the street were prohibited during the experiment. The speed of the first car was held constant by cruise control, and the temporal gap between the vehicles was manually adjusted based on feedback provided by a hood-mounted lidar (LightWare Optoelectronics SF30/C LiDAR). For the CAVE and HMD conditions, the parking lot was replicated virtually (Figure 3). The order of

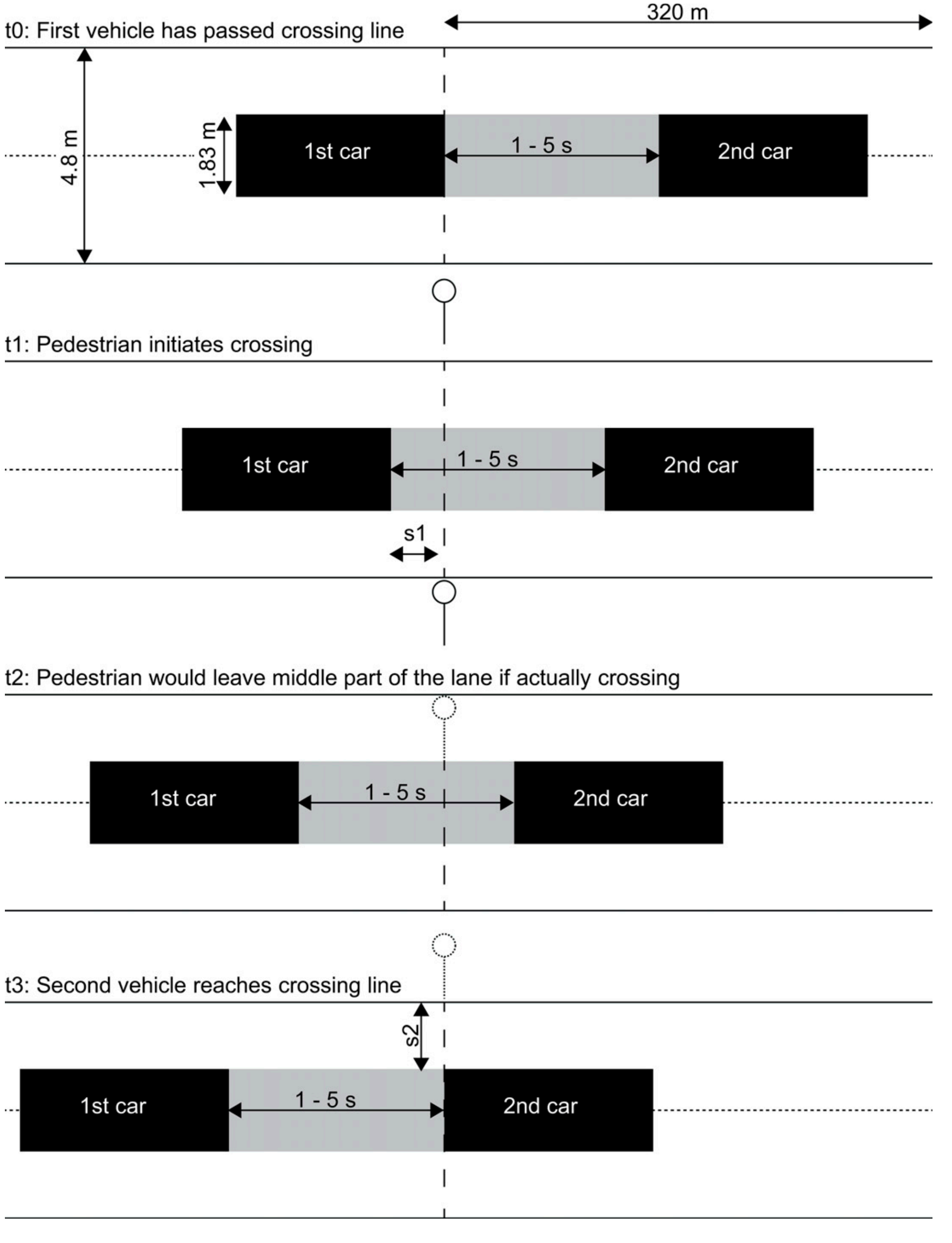

Figure 1. Schematic depiction of the crossing process. The dashed vertical line represents the pedestrian's hypothetical crossing trajectory; the dotted horizontal line refers to the center of the lane. CIT corresponds to the difference between t0 and t1 and can be obtained by dividing the distance s1 by the vehicle speed. PET corresponds to the difference between t2 and t3 and would be obtained by dividing s2 by the individual walking speed. s2 corresponds to the hypothetical distance to the middle part of the lane (gray), which the pedestrian would have covered at t3 if actually crossing. CIT = crossing initiation time; PET = postencroachment time.

Figure 2. Participant initiating crossing in the test track environment. Light barriers served to register the movement of stepping forward and to measure the speed and distance of the vehicles.

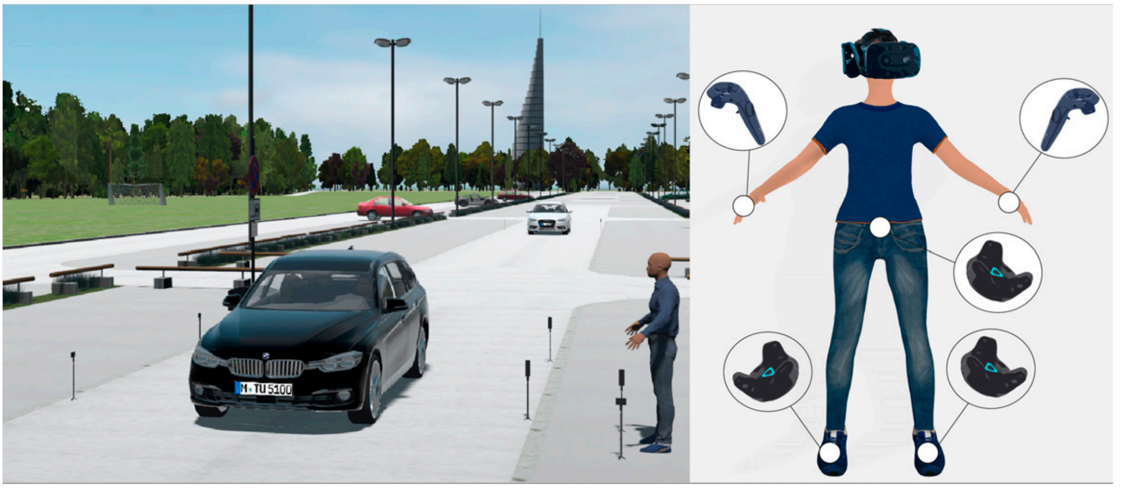

Figure 3. Virtual environment modeled after the test track (left) and the positions of tracking equipment used to visualize the ego avatar in the HMD condition (right). In the CAVE condition, virtual representations of the SMARTSPEED timing gates in front of the participant were replaced by physical substitutes, since the lack of a floor projection rendered them invisible in VR. CAVE = CAVE automatic virtual environment; HMD = head-mounted display; VR = virtual reality.

cars (Figure 2) was identical in all trials and virtual representations were chosen to match the color and model of the real vehicles. Based on speed profiles measured on the test track, virtual vehicles maintained a constant acceleration of 2.5 m/s^2 until reaching the target speed.

The CAVE corresponded to the setup described by Cavallo, Dommes, et al. (2019).

At a spatial resolution of 1400 × 1050 pixels, ten 1.88 × 2.55 m^2 projection modules formed a corridor in which participants could walk up to 7 m. Visuals were updated according to the position and rotation of the participant's head, tracked by eight Vicon Bonita cameras detecting markers attached to a helmet. No stereovision was provided. Sounds were emitted by 10 speakers located behind the projection modules.

In the HMD condition, participants wore an HTC Vive Pro headset, providing stereovision at a resolution of 1440 × 1600 pixels per eye and a 110° nominal FOV. An HTC Vive Wireless Adapter served to avoid the restrictions that a cable would have put on walking and rotation. An ego-avatar was displayed based on inverse kinematics, utilizing the position of the headset, three HTC Vive trackers attached to the participant's feet and belt, and two hand-held HTC Vive controllers (Figure 3). Integrated headphones displayed stereo auditory cues. Both simulators were installed within the same physical area in Versailles, France.

Experimental Procedure

After providing informed consent, participants read out letters (decreasing in height until a minimum of 6 mm) from a sheet of paper located a 4-m distance to confirm sufficient visual acuity. Individual walking speed was assessed by measuring the time needed to cover a 4-m span that was marked on the floor. Every participant walked this distance three times each at a leisurely and at a rapid gait. PET estimates are based on the overall mean of those trials.

To ensure that stepping forward triggered the light barriers on the test track, this movement was practiced several times. Additionally, each participant completed two familiarization trials, in which vehicles approached at 40 km/hr and formed gaps of 4 s and 2 s, respectively. To avoid triggering the light barriers multiple times, participants were instructed to complete a circle around them. Including the return of vehicles to their starting position, each trial took approximately 2 min. Before being debriefed, participants answered a questionnaire regarding perceived risk and the subjective agreement with their behavior in real-world traffic (compare Supplemental Material). The overall duration of the experiment was approximately 1 hr.

This research complied with the American Psychological Association Code of Ethics. It was conducted as part of a project that was approved by the ethics committee at the Technical University of Munich.

Participants

Ninety-seven young and healthy adults (20–35 years) were recruited via advertisements and personal contacts. Seven of them were excluded due to subsequent adjustments of the experimental protocol (n = 1), the mismatch of age criteria (n = 1), technical issues (n = 3), and the misunderstanding of instructions (n = 2). The remaining participants had a mean age of 27.7 (± 2.89) years. Each environment was presented to 15 males and 15 females.

Analysis

All analyses were performed in the R computing environment (R Core Team, 2020). To predict gap acceptance, CIT, and PET, we conducted mixed regression analyses based on the *lme4* (Bates et al., 2015) and *lmerTest* (Kuznetsova et al., 2017) packages. Fixed effects were calculated for the experimental environment, gap size, vehicle speed, and all two-way interactions. Speed was treated as an ordered variable and the environment was dummy coded, with the test track (labeled "TEST") as a reference. In addition to participant-dependent intercepts, random slopes for speed were included in the analyses of CIT and acceptance rates, since model comparison indicated a significant improvement in fit. Subjective ratings were analyzed by ordinal logistic regression (*ordinal* package; Christensen, 2019).

On the test track, CIT referred to the moment the light barrier was triggered by the movement of the participant's leg, whereas in the CAVE condition, only the head position was known. To correct for this offset, we calculated CITs in the HMD based on the positions of the head (CIT_{Head}), hip (CIT_{Hip}), and feet (CIT_{Foot}). We thereby considered all accepted trials except three cases in which the hip and feet position

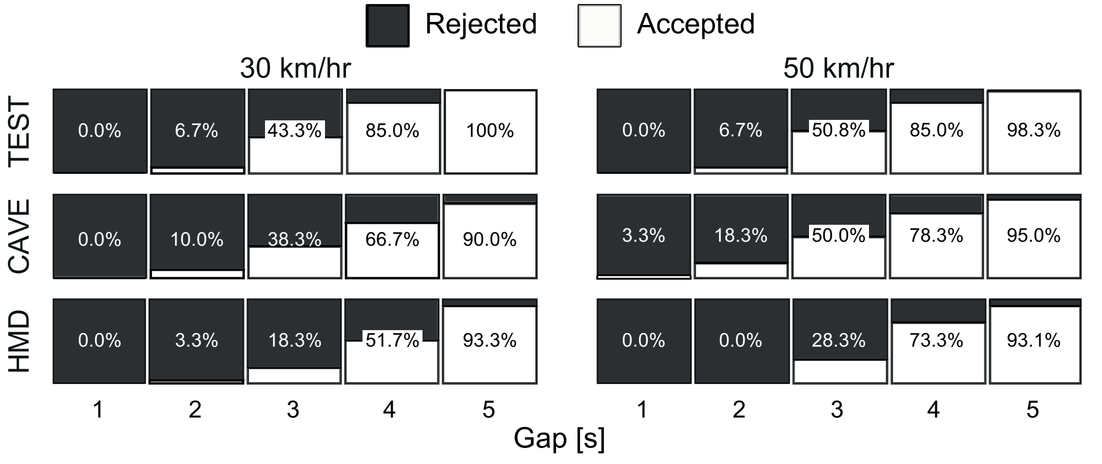

Figure 4. Observed gap acceptance rates as a function of the experimental environment, gap size, and vehicle speed. CAVE = CAVE automatic virtual environment; HMD = head-mounted display.

indicated that participants were partially standing in front of the light barrier. We used mixed linear regression (including participant-dependent intercepts) to predict the average of CIT_{Hip} and CIT_{Foot}, approximating the knee position for a straight leg. One observation was excluded based on Cook's distance exceeding a value of 2. In comparison to CIT_{Head}, an offset of 98.1 ms was observed—$F(1, 208) = 3170$, $p < .001$, marginal $R^2 = .939$—which was accordingly subtracted from CIT and added to PET in both simulators.

Data collected on the test track had previously been compared to crossing decisions in augmented reality (AR; Maruhn et al., 2020). Due to methodological differences including the number of participants and the experimental duration, the AR condition was no part of the present analysis.

RESULTS

Gap Acceptance

In all environments, larger gaps were more likely to be accepted (Figure 4). Across speeds and gap sizes, overall acceptance was highest on the test track (47.5%). In the CAVE, the overall rate was similar (45.0%), but gap size seemed less influential. In the HMD, participants were generally more reluctant to cross, accepting only 36.0% of all gaps.

Acceptance rates were examined by mixed logistic regression employing the "bobyqa" optimizer. The resulting model is included in the Supplemental Table S7. Figure 5 displays the predicted rates for each factor combination along with 95% prediction intervals. Decisions on gaps of 1 s, 2 s, and 5 s appear relatively clear, whereas uncertainty is larger for medium gaps. Distinct patterns occurred for the three environments: While 4-s gaps were mostly accepted on the test track, they seemed more ambiguous in VR. This in particular concerns the HMD, in which also gaps of 3 s were commonly rejected.

Differences between the three environments and their respective sensitivity to variations in speed and gap size become more evident in the analysis of simple slopes. The latter confirmed the significance of gap size in all environments, whereas an increase in acceptance rates at faster speed was significant only in the simulators (Table 1).

Acceptance rates did not differ significantly between the CAVE and the test track. In the HMD, acceptance was lower than on the test track for medium to large gaps at 30 km/hr, whereas differences in comparison to the CAVE mainly concerned small to medium gaps at 50 km/hr (Table 2).

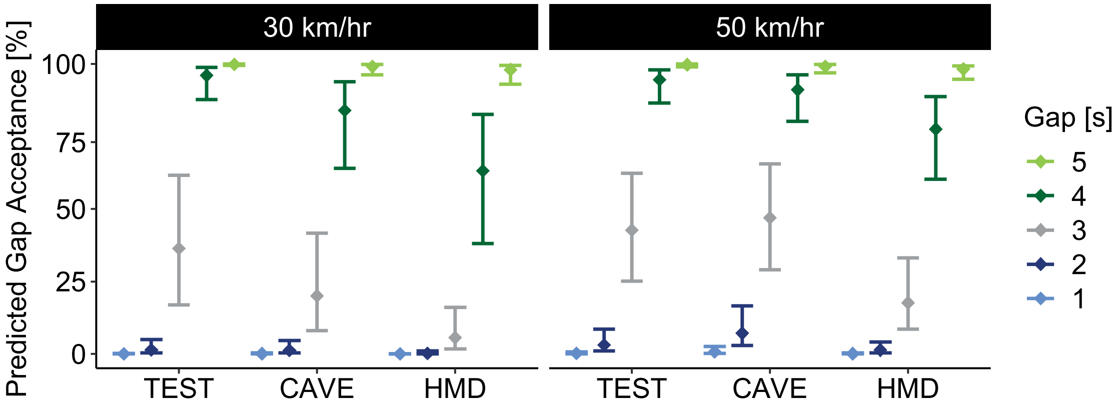

Figure 5. Acceptance rates as predicted by mixed logistic regression. Error bars represent 95% prediction intervals. Differences between the environments mainly concern medium gaps of 3 s and 4 s, which are also associated with the largest prediction uncertainty. CAVE = CAVE automatic virtual environment; HMD = head-mounted display.

TABLE 1: Simple Slopes Analysis Regarding Effects of Speed and Gap Size on Acceptance Rates in the Three Environments

		95% CI					
Variable	*B*	LL	UL	*SE*	β	*z*	*p*
Gap in TEST	3.743	3.038	4.563	0.387	10.681	9.652	<.001
Gap in CAVE	3.040	2.426	3.765	0.340	8.676	8.932	<.001
Gap in HMD	3.372	2.698	4.154	0.370	9.622	9.108	<.001
Speed in TEST	2.037	−.350	4.613	1.251	2.059	1.629	.103
Speed in CAVE	3.035	0.569	5.737	1.303	3.067	2.329	.020
Speed in HMD	3.068	0.276	6.098	1.469	3.100	2.089	.037

Note. β = standardized regression coefficient; *B* = unstandardized regression coefficient; CAVE = CAVE automatic virtual environment; CI = confidence interval of B; HMD = head-mounted display; LL = lower limit; *SE* = standard error of B; UL = upper limit.

Crossing Initiation Times

On the test track, CITs were mostly negative, indicating that participants initiated crossing before the first vehicle had passed them. In the simulators, in contrast, median CITs were close to 0 at 30 km/hr and positive at 50 km/hr (Figure 6).

In contrast to the other environments, larger gaps delayed crossing in the CAVE. This becomes particularly evident from the predictions obtained by mixed linear regression (Figure 7; model included in Supplemental Table S8). Higher speed, in contrast, delayed crossing initiation in all environments.

Simple slopes analyses confirmed an effect of speed in all environments (Table 3). The finding of delayed crossings at larger gaps, in contrast, was unique to the CAVE.

Simple slopes also confirmed that crossing in both simulators was delayed in comparison to the test track. This pattern was consistent across gap sizes and vehicle speeds. Differences between the simulators, in contrast, were insignificant (Table 4).

TABLE 2: Pairwise Comparisons of the Test Environments With Regard to Acceptance Rates.

Comparison	30 km/hr				50 km/hr			
	B	*SE*	*z*	*p*	*B*	*SE*	*z*	*p*
CAVE vs. TEST								
Gap: Small	0.375	1.137	0.330	.741	1.044	0.806	1.295	.195
Gap: Medium	−.814	0.758	−1.074	.283	0.166	0.558	0.297	.766
Gap: Large	−2.003	0.967	−2.072	.038	−.712	0.763	−.933	.351
HMD vs. TEST								
Gap: Small	−1.089	1.257	−.866	.387	−1.101	0.952	−1.156	.248
Gap: Medium	−2.110	0.808	−2.613	.009	−1.312	0.591	−2.220	.026
Gap: Large	−3.132	0.965	−3.246	.001	−1.522	0.759	−2.005	.045
CAVE vs. HMD								
Gap: Small	1.464	1.198	1.221	.222	2.145	0.883	2.429	.015
Gap: Medium	1.296	0.799	1.621	.104	1.478	0.583	2.535	.011
Gap: Large	1.129	0.826	1.366	.172	0.810	0.705	1.149	.250

Note. To account for multiple comparisons, *p*-values were compared to a Bonferroni-corrected significance level of α = .017. "Small," "medium," and "large" gaps correspond to gaps of 1.6, 3.0, and 4.4 s, representing the mean gap ± one standard deviation. *B* = unstandardized regression coefficient; CAVE = CAVE automatic virtual environment; HMD = head-mounted display; *SE* = standard error of B.

Postencroachment Times

PET represents a temporal buffer between a crossing pedestrian and an approaching vehicle. Negative values imply a collision if participants had crossed at their average walking speed. As Figure 8 shows, this mainly concerns gaps below 3 s, whereas larger gaps seem passable if crossing is initiated on time. Judged by PET, 11.5% of crossings (n = 31) in the CAVE were unsafe, whereas this rate was lower in the other environments (HMD: 2.8%, n = 6; TEST: 3.8%, n = 11). This coincides with the elevated propensity to accept small gaps in the CAVE (Figure 4). However, while

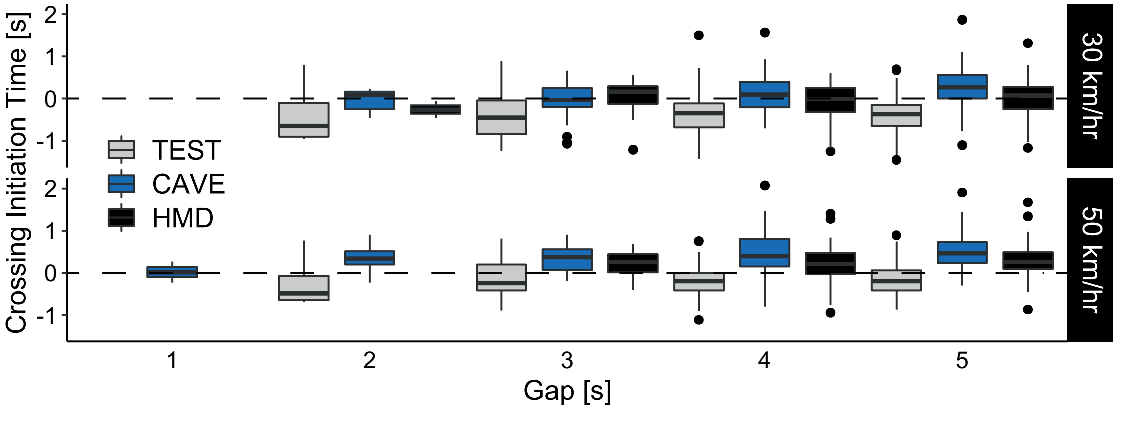

Figure 6. Observed CIT as a function of the experimental environment, gap size, and vehicle speed. Negative values indicate that participants started crossing before the first vehicle had completely passed them. CAVE = CAVE automatic virtual environment; CIT = crossing initiation time; HMD = head-mounted display.

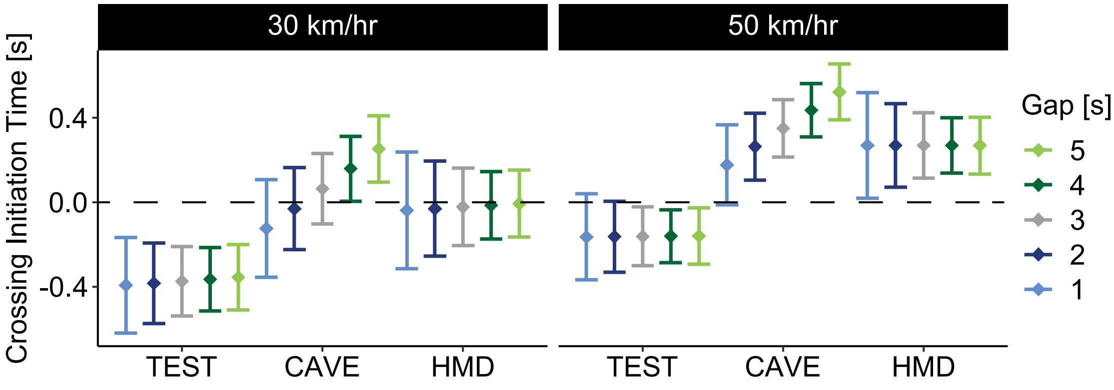

Figure 7. CIT as predicted by mixed linear regression. Error bars represent 95% prediction intervals. Negative values indicate that participants started crossing before the first vehicle had completely passed them. In contrast to the other environments, CIT in the CAVE seems to be strongly influenced by gap size. In all conditions, crossings were initiated later if vehicles approached faster. CAVE = CAVE automatic virtual environment; CIT = crossing initiation time; HMD = head-mounted display.

TABLE 3: Simple Slopes Analysis Regarding Effects of Speed and Gap Size on CIT in the Three Environments

		95% CI						
Variable	*B*	LL	UL	*SE*	β	*t*	*df*	*p*
Gap in TEST	0.009	−.043	0.061	0.027	.015	0.349	658	.728
Gap in CAVE	0.095	0.042	0.147	0.027	.155	3.538	659	<.001
Gap in HMD	0.008	−.057	0.073	0.033	.013	0.243	671	.808
Speed in TEST	0.237	0.006	0.467	0.118	.223	2.001	527	.046
Speed in CAVE	0.310	0.080	0.538	0.117	.293	2.650	452	.008
Speed in HMD	0.316	0.070	0.559	0.125	.298	2.518	543	.012

Note. β = standardized regression coefficient; *B* = unstandardized regression coefficient; CAVE = CAVE automatic virtual environment; CI = confidence interval of B; CIT = crossing initiation time; *df* = degrees of freedom calculated based on Satterthwaite's method; HMD = head-mounted display; LL = lower limit; *SE* = standard error of B; UL = upper limit.

2-s gaps were also accepted on the test track, participants in this case were at least partially able to compensate for the reduced time budget by starting early, resulting in more positive PETs.

Since crossings were not actually performed, PET estimates are a direct function of CIT, gap size, and walking speed. While PET thus unsurprisingly increased with gap size (Table 5), mixed linear regression also revealed interactions between the environment and both speed and gap size (Supplemental Table S9). Higher speed significantly reduced PETs in both simulators, but not on the test track (Table 5). Since the model accounts for the acceptance of smaller gaps at 50 km/hr, this observation suggests that speed variations affected CIT more clearly in the simulators.

For medium to large gaps, PETs in the CAVE were smaller than on the test track, whereas in the HMD, effects were significant only for large gaps and at 50 km/hr. Differences between the simulators were insignificant (Table 6).

TABLE 4: Pairwise Comparisons of the Test Environments With Regard to CIT.

	30 km/hr					50 km/hr				
Comparison	B	*SE*	*t*	*df*	*p*	B	*SE*	*t*	*df*	*p*
CAVE vs. TEST										
Gap: Small	0.319	0.165	1.934	320	.054	0.384	0.137	2.806	312	.005
Gap: Medium	0.439	0.124	3.538	128	<.001	0.509	0.102	4.987	118	<.001
Gap: Large	0.559	0.110	5.085	82	<.001	0.633	0.092	6.882	82	<.001
HMD vs. TEST										
Gap: Small	0.456	0.188	2.427	430	.016	0.346	0.166	2.088	492	.037
Gap: Medium	0.403	0.134	3.006	167	.003	0.390	0.113	3.446	174	<.001
Gap: Large	0.350	0.111	3.162	84	.002	0.433	0.092	4.700	83	<.001
CAVE vs. HMD										
Gap: Small	−.137	0.190	−.723	427	.470	0.039	0.159	0.243	449	.808
Gap: Medium	0.036	0.135	0.266	170	.791	0.119	0.111	1.071	161	.286
Gap: Large	0.209	0.111	1.874	86	.064	0.199	0.093	2.151	83	.034

Note. To account for multiple comparisons, p-values were compared to a Bonferronicorrected significance level of α = .017. "Small," "medium," and "large" gaps correspond to gaps of 1.6, 3.0, and 4.4 s, representing the mean gap ± one standard deviation. *B* = unstandardized regression coefficient; CAVE = CAVE automatic virtual environment; CIT = crossing initiation time; *df* = degrees of freedom calculated based on Satterthwaite's method; HMD = head-mounted display; *SE* = standard error of B.

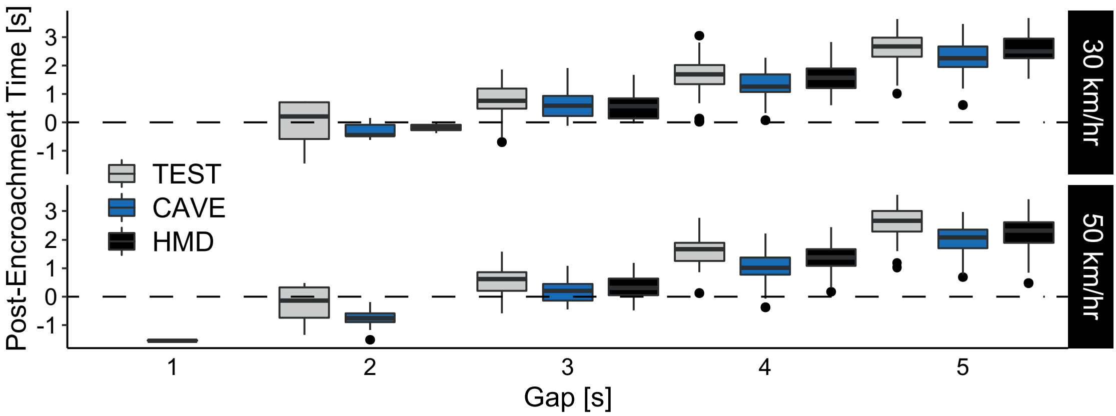

Figure 8. Observed PET as a function of the experimental environment, gap size, and vehicle speed. Negative values indicate a hypothetical collision that would have occurred if a participant had actually started to cross at an average speed corresponding to the individual speed measured prior to the experiment. CAVE = CAVE automatic virtual environment; HMD = head-mounted display; PET = postencroachment time.

Subjective Responses

Questionnaires were analyzed by ordinal regression. In comparison to both simulators, participants on the test track judged their decision to cross as safer (CAVE vs. TEST: $z = -3.954$, $p < .001$; HMD vs. TEST: $z = -1.668$, $p = .003$) and a collision as less likely (CAVE vs. TEST: $z = 2.128$, $p = .033$; HMD vs. TEST: $z = 2.105$, $p = .035$). Although descriptively, they indicated more frequently that a potential collision would have been "very dangerous," differences in comparison to the simulators were insignificant in this

TABLE 5: Simple Slopes Analysis Regarding Effects of Speed and Gap Size on PET in the Three Environments

Variable	*B*	95% CI LL	95% CI UL	*SE*	β	*t*	*df*	*p*
Gap in TEST	0.973	0.921	1.026	0.027	.846	36.060	679	<.001
Gap in CAVE	0.903	0.852	0.957	0.027	.786	33.233	685	<.001
Gap in HMD	0.985	0.921	1.052	0.034	.857	29.266	684	<.001
Speed in TEST	−.151	−.382	0.080	0.118	−.076	−1.276	677	.202
Speed in CAVE	−.358	−.589	−.121	0.116	−.178	−3.074	676	.002
Speed in HMD	−.384	−.628	−.128	0.125	−.190	−3.064	677	.002

Note. β = standardized regression coefficient; *B* = unstandardized regression coefficient; CAVE = CAVE automatic virtual environment; CI = confidence interval of B; *df* = degrees of freedom calculated based on Satterthwaite's method; HMD = head-mounted display; LL = lower limit; PET = postencroachment time; *SE* = standard error of B; UL = upper limit.

TABLE 6: Pairwise Comparisons of the Test Environments.

Comparison	30 km/hr *B*	30 km/hr *SE*	30 km/hr *t*	30 km/hr *df*	30 km/hr *p*	50 km/hr *B*	50 km/hr *SE*	50 km/hr *t*	50 km/hr *df*	50 km/hr *p*
CAVE vs. TEST										
Gap: Small	−.229	0.178	−1.285	272	.200	−.300	0.160	−1.876	230	.062
Gap: Medium	−.286	0.141	−2.036	121	.044	−.437	0.130	−3.371	109	.001
Gap: Large	−.344	0.128	−2.682	85	.009	−.574	0.121	−4.732	85	<.001
HMD vs. TEST										
Gap: Small	−.273	0.200	−1.362	371	.174	−.203	0.186	−1.092	363	.275
Gap: Medium	−.173	0.150	−1.156	151	.250	−.264	0.139	−1.903	141	.059
Gap: Large	−.073	0.129	−.570	87	.570	−.325	0.121	−2.679	85	.009
CAVE vs. HMD										
Gap: Small	0.043	0.202	0.215	373	.830	−.097	0.180	−.539	332	.590
Gap: Medium	−.113	0.151	−.752	154	.453	−.173	0.137	−1.261	135	.210
Gap: Large	−.270	0.130	−2.087	89	.040	−.249	0.122	−2.041	86	.044

Note. To account for multiple comparisons, p-values were compared to a Bonferroni-corrected significance level of α = .017. "Small," "medium," and "large" gaps correspond to gaps of 1.6, 3.0, and 4.4 s, representing the mean gap ± one standard deviation. *B* = unstandardized regression coefficient; CAVE = CAVE automatic virtual environment; *df* = degrees of freedom calculated based on Satterthwaite's method; HMD = head-mounted display; *SE* = standard error of B.

respect (CAVE vs. TEST: $z = -.939$, $p = .052$; HMD vs. TEST: $z = -.688$, $p = .152$). Regardless of the minimal risk of physical harm, a majority considered a potential collision at least "dangerous" in the simulators (Figure 9).

In comparison to the test track, participants in the HMD rated their behavior as more cautious ($z = 2.450$, $p = .014$) and felt they needed more time ($z = -2.172$, $p = .030$), although decisions were not rated as significantly harder. No differences

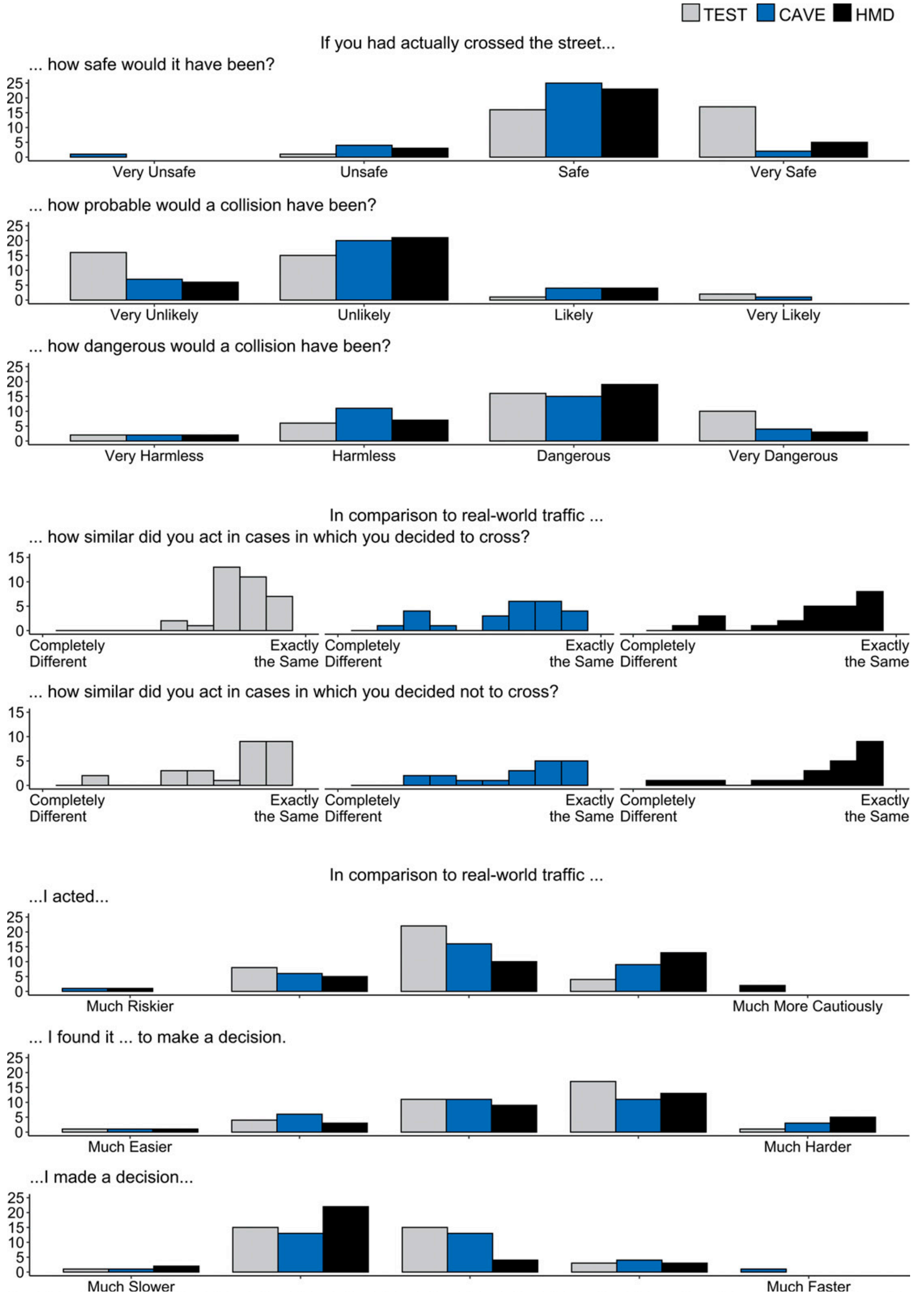

Figure 9. Questionnaire results regarding subjectively perceived risk and the agreement with real-world traffic.

emerged between the test track and the CAVE (all $p \geq .354$).

Across environments, participants stated that their decisions reflected real-world behavior but highlighted a lack of contextual information such as time pressure and alternative crossing options. Several individuals noted that they would usually adjust their walking speed to compensate for small gaps. Contrasting the observed acceptance rates, participants on the test track suggested they would take higher risks in real world, whereas those in the simulators tended to think they would behave more cautiously.

DISCUSSION

VR is a popular tool to investigate pedestrian behavior (Schneider & Bengler, 2020). The meaningfulness of related studies, however, crucially depends on the extent to which observations can be generalized to nonvirtual environments. Besides effects of the experimental setting, such transfer may be jeopardized by a number of perceptual and behavioral modifications in VR (Feldstein, 2019; Renner et al., 2013).

Particularly in the HMD, participants were more reluctant to cross. Although consistent with Bhagavathula et al. (2018), this contradicts previous findings of more frequent crossings in HMDs than in CAVEs (Cavallo, Dang, et al., 2019; Mallaro et al., 2017). Differences may be related to the experimental task: In line with Bhagavathula et al. (2018), we evaluated crossing intent rather than actual crossings, which caused participants to experience at most brief episodes of walking. Although avoiding the inference of a cable by means of a wireless adapter, uncertainty about their physical surroundings may have prevented fast movements and thus resulted in more cautious behavior.

Using a step-back technique, Feldstein and Dyszak (2020) found the minimal time-to-contact acceptable for crossing to average around only 2 s in an HMD. Values of 2.8 s in the nonvirtual environment, in contrast, were more comparable to the present findings. Interestingly, this may imply that participants in VR are more reluctant to make a decision—regardless of whether it concerns the acceptance or rejection of a gap. Such reluctance may result from restricted or biased sensory information and is consistent with the higher confidence stated on the test track. As indicated by smaller CITs, such confidence also seemed to accelerate decisions. Since at least the HMD group expressed awareness for their reluctance and delayed reactions, self-reports may support the interpretation of observational data in future studies.

In both simulators, participants accepted smaller gaps at higher speed, indicating that they relied on spatial rather than temporal margins (Feldstein & Dyszak, 2020). In this context, a lack of relevant visual cues in VR may result in an underestimation of vehicle speed and consequently an overestimation of the time to arrival (TTA; Petzoldt, 2014). Cavallo and Laurent (1988) found TTA to be consistently underestimated on a test track, but speed effects occurred only for impoverished visual conditions. Similarly, Feldstein (2019) suggested effects of velocity only for compromised visual perception. Hence, our findings imply that the perceptual accuracy provided by current pedestrian simulators is still insufficient to replicate real-world behavior. Restricted visual resolution, for instance, may hamper the assessment of velocities or gaps at larger distances, shortening the effective viewing time for higher speeds: If precise estimates were possible within a range of 100 m, decisions could be based on a viewing time of 12 s at 30 km/hr, but only on 7.2 s at 50 km/hr.

It is important to note that biased speed perception may compensate for further differences between virtual and nonvirtual environments, as demonstrated by the higher agreement of acceptance rates at 50 km/hr (Figure 5). The underlying mechanisms, however, may differ: On the test track, an accurate perception of speed and distance can lead to reasonably accepting a gap, whereas the same decision could result from an underestimation of both in VR.

Difficulties in predicting TTA, related to the moment the first vehicle passes, may also explain the delayed crossing initiation in VR. Alternatively, being more risk-aware and attentive when confronted with actual vehicles, participants on the test track may have started crossings earlier to extend the safety margin. This explanation, however, neglects the greater difficulty that was reported in identifying crossing opportunities in the HMD. Particularly the relationship between gap size and CIT in the CAVE is noteworthy: For small gaps, predicted CITs were similar to the HMD, whereas crossings were further delayed at larger gaps. Due to the missing ground projection, cars in the CAVE were not visually represented while directly in front of the participant. Hence, one may reasonably initiate crossing only after the first car has passed and reappeared on the left. Larger gaps implying larger safety margins might have reduced urgency. This, however, equally affects the other environments, in which CIT seemed unrelated to gap size. Hence, this finding deserves further consideration in future research, also accounting for the prediction uncertainty associated with low acceptance rates.

LIMITATIONS AND OUTLOOK

As indicated by relatively large confidence and prediction intervals, the preciseness of predicted crossing behavior suffers from low acceptance rates at small gaps. The comparison of test environments was additionally affected by the limited sample size and individual differences in a between-group design. To minimize statistical noise at the given resources, the sample was restricted to young and healthy adults. Since other groups might react differently to the technical setup (Cavallo, Dang, et al., 2019; Maillot et al., 2017), the present results should be extended to populations such as children and the elderly.

Data were collected within an international collaboration. Behavioral adaptations in street crossing have been associated with cultural individualism (Pelé et al., 2017), which is usually assumed similar across Western Europe. A few existing comparisons between European countries tentatively suggest Germans to be more patient (Güss et al., 2018) and risk aversion to be comparable (Schleich et al., 2019). Adding to similar legal standards, cultural differences seem thus unlikely to produce the observed pattern of more reluctant crossings in VR.

Due to technical restrictions, the mechanism for detecting crossing initiation differed between environments. The resulting offset was modeled based on observations in the HMD group, which relies on similar movement patterns in both simulators. Although we were unable to account for individual fluctuations, the corresponding regression model yielded a marginal R^2 of 93.9%, implying a relatively accurate prediction and supporting the feasibility of the chosen procedure.

Lastly, the experimental context may have affected behavior across environments, for example due to observer effects and social desirability, but also because of the simplified scenario. Signaling crossing intent differs from actual crossing (Lobjois & Cavallo, 2009; Morrongiello et al., 2015). The lack of walking movements prevented evasive speed adjustments, rendering PET estimates for a given individual a direct function of CIT and gap size. Although actual crossings are arguably closer to real-world demands, decision tasks are common in pedestrian research (Schneider & Bengler, 2020), among others because they pose minimal risk in nonvirtual environments. The present results should therefore be understood in this particular context.

Generalizing to real-world traffic, one must deal with increased complexity due to multidirectional traffic, various distractors, and a lack of predictability (Schneider & Li, 2020). Our results imply that virtual and nonvirtual environments yield different conclusions when investigating crossing decisions, but it is unclear to which extent either of them is congruent with uninstructed behavior in naturalistic traffic. Reliable conclusions, in particular regarding the prediction of safety-relevant outcomes, consequently require further comparisons to real-world data.

With the above reservations, the present study qualifies statements on the generalizability of VR-based results in the context of pedestrian research. The systematic comparison of two common simulator types to a test track yielded distinct findings in the three environments for all dependent measures. While various advantages nonetheless render VR an important research methodology, our findings should inform the conclusions drawn from future analyses, for example by accounting for a higher sensitivity to speed variations and the greater uncertainty associated with crossing decisions.

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KEY POINTS

- To evaluate the adequacy of virtual environments for pedestrian research, crossing decisions were compared on a test track, in a CAVE and in a HMD.
- Participants on the test track initiated crossings earlier and were more confident of their decision. Particularly in the HMD, they were more reluctant to cross.
- Changes in the speed of approaching vehicles affected crossing decisions more strongly in the two virtual environments than on the test track.
- In contrast to both the test track and the HMD, crossing initiation in the CAVE was delayed for larger gaps.

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SUPPLEMENTAL MATERIAL

The online supplemental material is available with the manuscript on the HF website.

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