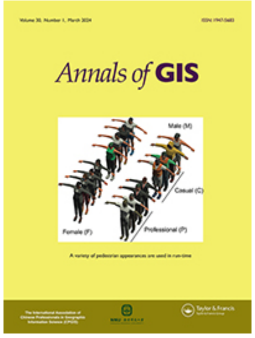

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Evoking embodiment in immersive geosimulation environments

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ABSTRACT
We tackle the issue of how one might close the gap between geographies of people's behavioural experiences and computer models designed to depict those geographies as simulations. We introduce the idea of *Immersive Geosimulation Environments* (IGEs) as a methodology for coupling spatial behaviour directly to simulation by providing access to (and interaction with) geographic information in ways that elicit user response as fully realized spatial spatial experiences. Importantly, IGEs allow spatial behaviour to be embodied to geosimulation, rather than remaining vicarious to its geography. To examine the utility of IGE methodology, we demonstrate a worked example in the safety science of road-crossing. We present an end-to-end IGE testbed for examining pedestrian – traffic – environment interactions at the roadside. The IGE is designed to achieve congruence between reality and simulation across two related channels. *Congruence in fidelity* tackles adherence to real-world counterparts, i.e. the condition that IGE elements should function with authenticity to real-world geographies. *Congruence in verisimilitude* addresses how realistic IGEs seem to the individual user experience, i.e. an IGE's ability to evoke natural spatial behaviour within model scenarios. Our results point to the significance of embodiment in closing the reality gap. We posit that facilitating the formation of action maps, which relate models to users' behaviour, could be key in providing functionally embodied geographic information systems and geosimulation systems.

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Geosimulation, embodiment, virtual reality; geographic automata systems; sim2real, pedestrian; traffic; spatial behavior; geo-CHI

'This town don't feel mine/I'm fast to get away/Far' (Deftones 1997)

Introduction

Geosimulation is often proposed as a computational test bed for exploring phenomena that span multiple scales of space and time (Benenson and Torrens, 2004). One of the advantages of the geosimulation approach lies in its agility to represent thorny issues that arise from complex dynamics among 'intervening geographies', i.e. from processes that flit between scales (Torrens 2004). Methods for geosimulation have traditionally coalesced around relatively 'big' geographies: typical applications include phenomena that shape urban and neighbourhood areal geographies, i.e. wide-area geographies considered over longitudinal periods of time (see Batty and Torrens (2005), Benenson et al. (2002), Clarke et al. (1997), Li and Yeh (2000), Shiode and Torrens (2008), Torrens (2006a, 2006b), White and Engelen (2000) for archetypes). However, the original concept for geosimulation emphasized its potential for representing hyper-local behaviours that bubble-up and play out between individuals and others at 'small' geographies, even down to the individualized conduct that governs spatial agency as it unfolds in fleeting rivulets of space and time (Albrecht 2005; Torrens 2007). 'Small geography' insight is comparatively well-developed in theoretical form (Golledge 1978), but a matching counterfoil in geosimulation is often difficult to advance. The reasoning behind this is complicated (Allen and Torrens 2005; Goodchild and Mark 1987; Zou et al. 2012), but it is operationally sourced in a paucity of empirical data at matching scales and the related problem of building model representations of processes, phenomena, entities, and relationships that are typified by high uniqueness and independence (Torrens 2018a). We make the observation in this paper that the rather recent commercial popularization of virtual reality (VR) systems provides new simulation media that geosimulation could avail of in advancing towards authentic representations of small geography. Chiefly, we see novel opportunities to connect geosimulation directly to small geographies with one-to-one mappings that offer hitherto unseen insight into the geography underpinning phenomena of study. Our thesis is that VR could enable geosimulation users to be immersed directly and experientially in the simulated geographies that the simulation produces. We consider the feasibility of achieving such immersion in real-time, to allow users to become

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directly embodied relative to geosimulated phenomena. We introduce a new approach that merges geosimulation with VR to produce three-dimensional hybrids of real-world and simulated process and phenomena environments. We consider this combination as 'Immersive Geosimulation Environments' (IGEs) and we take up the issue of how well IGEs perform as authentic models of real-world small geographies, and as useful media for simulation-based experiments. In doing so, we focus specifically on the feasibility of using IGEs to build simulation-assisted understanding of small geographies.

Aims, objectives, and opportunities

Our analytical discussion focuses on the potential for IGEs to advance two important dimensions of congruence between the model geographies and geographic reality: (1) *congruential fidelity* and (2) *congruential verisimilitude*. Specifically, in this paper we examine how well IGEs might facilitate congruence to small geographies of individual people, their body language, their perception and uptake of geographic information in local proxemics, and the processes that drive these processes upand down-scale to coarser geographies of streetscape environments and roadside traffic. This necessitates that we develop new systems for building GIS on novel streaming data that typically come from hyper-local sensing and computing and that can supply empirical resources at relatively high resolutions of space and time that traditionally have been unavailable to geosimulation.

One way to frame this objective is through causality in knowledge generation (Schatzki 1991) in simulation-based engineering and science (Oden et al. 2006). Consider, as an illustrative example, the current approach of machine learning that is often termed as 'sim2real' (Doersch and Zisserman 2019). Sim2real has emerged as way to leverage the wide experimental dimensionality of procedural simulation (and animation) as a medium for transfer learning. This is convenient, but seems logically problematic as a means to uncover truth: models are simulacra and training 'other models' (machine learning routines) on simulacra (Baudrillard 1994; Gibson 1984; Stephenson 1993) leads to problematic issues of artificiality creep in any deduced systems. The phenomenon of machine learning hallucinations – generative results with no authenticity to reality – is one outcome of this problem. In this paper, we explain that valuable (and *grounded*) insight can be derived for geographic phenomena by working in the other direction, via reality-to-simulation ('real2Sim') pathways. We envisage IGEs as one such pipeline for real2sim. In particular, we use real human participation to drive process dynamics (in simulation), especially those at small geographies that defy parsimony in definition as models, algorithms, or heuristics.

Thus, we approach our aim of enabling real2sim congruence in IGEs with three interwoven objectives. Our first objective is to increase *fidelity-based realism* of geosimulation, particularly for use scenarios in VR. This requires IGE methods that can usefully convince participants, per-application scenario, that the virtual spaces, objects, processes, and phenomena that they encounter and explore are faithful representations of real-world counterparts. We adapt geosimulation for local action to accomplish this. We specifically target *geographic fidelity* (including stereo visual and auditory fidelity). Rather than validating fidelity against secondary data (Torrens 2011), e.g. through spatial analysis (Nara and Torrens 2007) or trajectory analysis (Nara and Torrens 2011), we target (1) users' self-reported assessment of fidelity while in simulation trials, (2) through in-simulation testing, and (3) via empirical user task performance metrics.

Our second objective is to address *realism in verisimilitude*, particularly the verisimilitude of user experiences within geosimulation. We are mindful that geographic verisimilitude is a special case, and our IGEs must engage users' *typical spatial* faculties, behaviours, and skills. Invariably this invokes issues of geographic computer–human interaction (geo-CHI). In essence, we take aim at the traditional 'weak' approach in geosimulation (such as moving dots on a screen and pixel-based pattern emergence). Instead, we establish an objective of supporting 'strong' verisimilitude. Specifically, we wish to allow users to transpose themselves directly into the geosimulation as a tangible experience, as involved and embodied participants. This establishes a much higher threshold for verisimilitude than traditional geosimulation usually would attempt.

Third, we seek to embody users' behavioural purpose in the IGE (rather than simple vicarious control of their camera). Our target, then, is to establish user immersion with *direct* (rather than abstract) encounters (Dourish 2001) (p. 100) to geographic information of the VR environment as well as the geosimulation that animates its geography and behaviour-driven entities. We address this by generating a virtual test bed for road-crossing experiences designed to evoke fleeting decisions of road-crossing behaviour as it unfolds in small (often harried) envelopes of space and time (Torrens & Kim 2024). The test bed is presented to the user via head-mounted display (HMD) as a mobile Virtual Reality Environment (mVRE) of a suburban roadside, thereby allowing the user to experience the geosimulation directly through their natural spatial faculties for perception, action, and cognition.

Fulfilling these objectives creates a set of opportunities for geographic information science (and perhaps also for geography). The first opening is to address the current gap that geographic simulation techniques have in experiential parity with real-world geographic information. This includes geosimulation, VGEs, and other forms of geo-CHI such as mixed reality (MR) and extended reality (XR). In particular, we recognize that novel forms of immersively sourced data are newly available in detailed form (often streamed over high-bandwidth and low-latency communications (Torrens 2022b) that IGEs could support if developed to meet those data on their 'own terms'.

The second opportunity is the latent expositional advantages that could accrue from advancing *empirical* understanding of small geographies, particularly in drawing empiricism and theory into closer explanatory alignment. Consider, for example, that small geographies play a significant role in road-crossing. Observational evidence in safety science (Liu and Tung 2014) indicates that crossing pedestrians are highly reliant upon a quick-settled calculation (risk analysis) of the available speed and time that they have to cross in momentary crossing gaps. In some ways, this involves a fleeting but important transition from large to small geography: allocentric analysis of site factors, as well as an ego-centred check of dynamic traffic gaps against one's own sense of their abilities and the site-situational opportunity to proceed through the gap (Griffin et al. 2007). Understanding the interplay between these geographies could provide insight into prospect theory (Kahneman and Tversky 1979; Sueur et al. 2013), and its framing of how pedestrians exhibit visible signs of anticipation and of caution when crossing, and how those signs are to then be picked up and interpreted by other people around them at the roadside (Harrell 1991). This has significant practical relevance: there are large variations in crossers' success in evaluating risk based on speed and delay time (Underwood et al. 2007). Young crossers perform well in assessing small geographies, but in ego-checking they overestimate the skill they have to proceed safely based on that information. On the other hand, it seems that very senior crossers often misjudge the spacing, timing, or both available to them, and thus cross with incorrect information that puts them at risk, essentially by accepting gaps that are not safe (Torrens 2012). In other words, they misinterpret the geographic information that is available ambiently and proximally (Torrens & Kim 2024). In the safety science literature, there is no clear answer as to why this is the case, partially because factual behavioural evidence that is 'close to' crossers and the information they have immediately on hand are hard to come by.

A third opportunity presents around fostering improved exchange between reality and simulation for methodological purposes. Because spatial behaviour factors of crossing phenomena are largely opaque to any sort of academic inquiry or engineering intervention on the ground, IGEs could be considered as what-if laboratories for geographic research in their places. Consider that uncovering spatial behaviour in real life is prone to immutable barriers of observational bias (whether performed by human observers or by machine learning). There are also practical difficulties in carrying out behavioural research in busy populated urban environments, where crossers are easily obscured from view in scenes with even a few people or vehicles. Alternatively, IGE-based experiments can provide targeted experimental levers for studying spatial behaviour and they can do so with complete informational recall. We note that the use of IGEs to support real-world experimentation is particularly promising for studying spatial behaviour of the elderly (Liu and Tung 2014; Maillot et al. 2017) (who may experience reduction in spatial faculties at very senior years) and of children (Schwebel, Gaines, and Severson 2008; Schwebel et al. 2016; H. Wang et al. 2022) (who are developing and honing their spatial behaviour relative to geographic information that they encounter). It is often difficult to recruit from these groups and challenging to build representative samples of the difficulties that they face when crossing. IGEs, by providing easy access to what-if testing of crossing infrastructure, environmental conditions, synthetic entities, and model processes, could make it easier to build wide-reaching experimental insight with small samples of user behaviour, in ways that would not be feasible, say, by ethnographic observation alone.

Methods

Our methodology focuses on bringing together a few geographic information technologies, but doing so with parity of data exchange, run-time computation, and user experience. Intermingling these three with equivalence in interoperability leads us to developing IGEs (Figure 1) from a set of interlocking engineered hardware technology, data science, geographic information science, algorithm developments, and computer graphics (see Figure 2 for an overview).

Creating a hybrid virtual-tangible space for human users to roam and explore

As a base Virtual Geographic Environment (VGE), we developed a static three-dimensional simulated urban scene composed of built components and traversable spaces (Figure 3) to which we subsequently add dynamics elements. Crucially, we also established a companion and *tangible* physical environment in a studio space, which users could roam with 1:1 geographic matching to the IGE. This is important, as the VGE thus becomes both virtual and corporeal, with simultaneous embodiment in both geographies. The IGE was delivered to users via

Figure 1. Local action models can embody users and beatles in IGEs with high fidelity and high verisimilitude to real-world (and what-if) scenarios of human experiences.

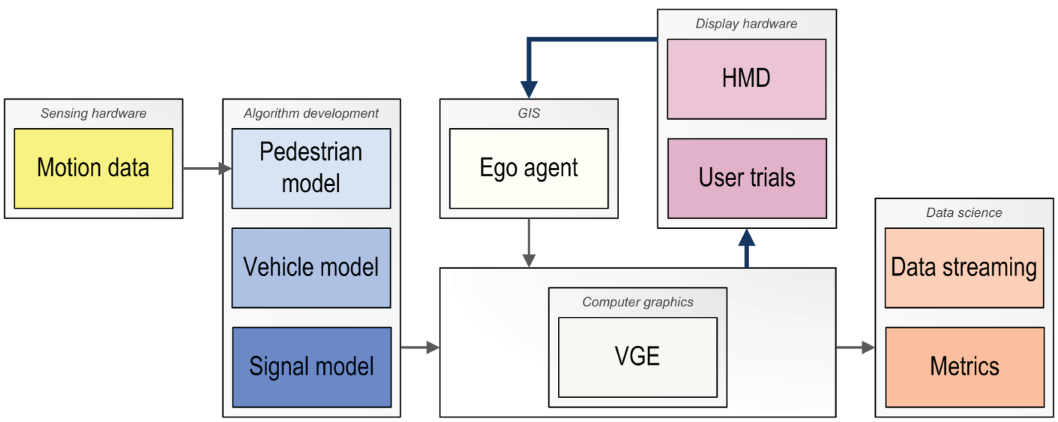
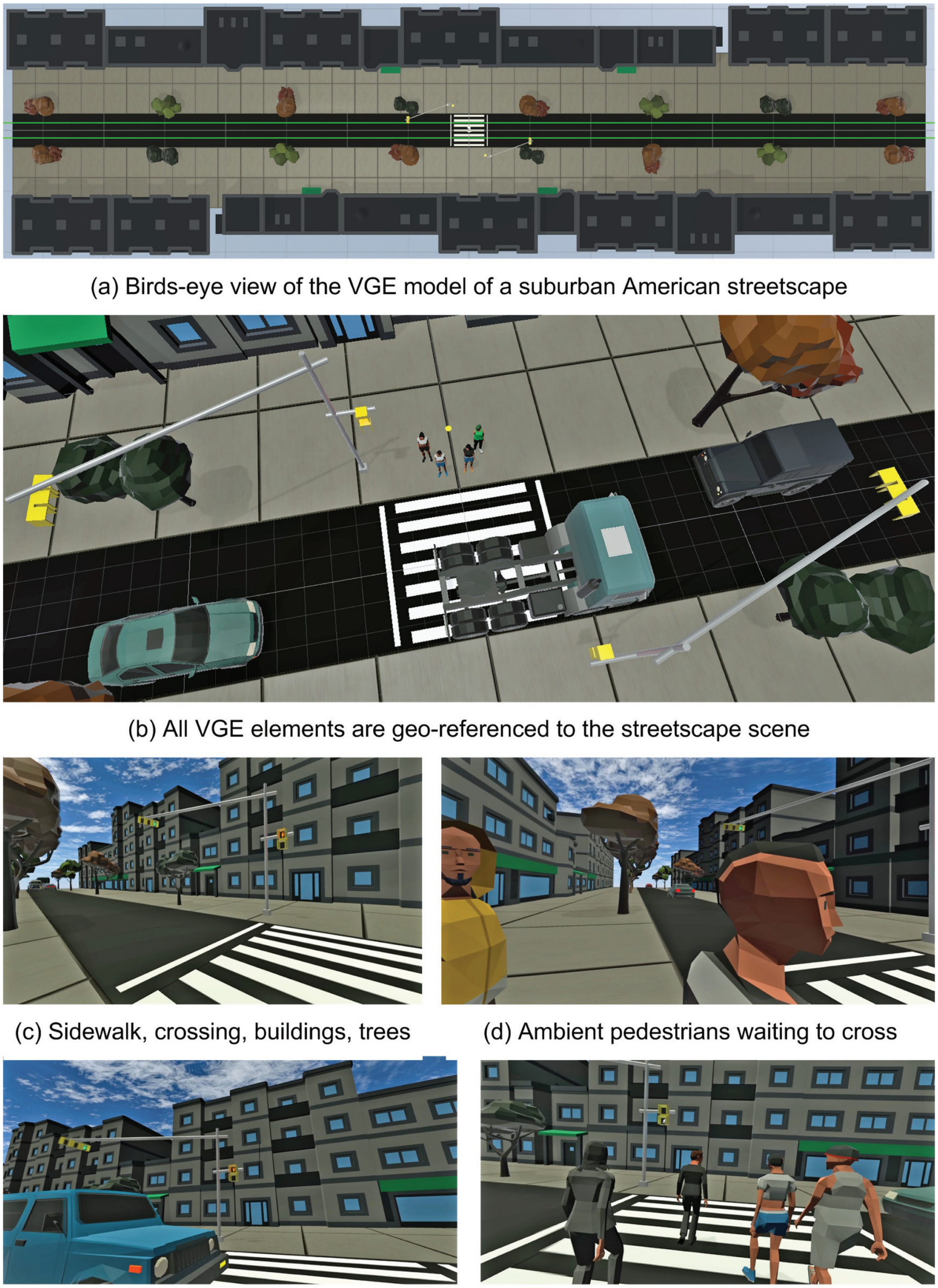


Figure 2. The broad methodological pipeline for the IGE road-crossing test bed.

wireless HMD, with the result that audio and visuals were provided solely by virtual geography.

We designed the IGE to represent a suburban American roadside. The virtual components of the IGE were *rendered* for parts of the simulated city far beyond the road-crossing, and if users ventured into a portion of the IGE that was not physically matched to our studio room, a geo-fence visualization was displayed in the HMD, urging the user against proceeding further. In physical terms, the (virtually) traversable IGE corresponded to a two-lane *roadway*, 5.5 metres wide with a mid-road 27.5 m^2 *signalized zebra crossing* (Figure 3). Each lane of the road spanned 2.75 metres wide (common design specifications for the United States) and 150 metres long (to match available space in our studio). At the crossing roadside, we included *traffic poles*, *traffic lights*, and *crossing signals*. (Because the crossing also includes pedestrian signals, we refer to the zebra crossing and adjacent signals site as a 'PELICAN', i.e. pedestrian light controlled.) A partially cloudy *skybox* was chosen to improve immersion, and *lighting effects* (primarily shadowing) were used. Pedestrian crossing and traffic signals were placed five metres and three metres off the ground respectively (Figure 3). Each was rendered with a dynamic signal display that was programmed by state transition with a corresponding animation. A custom *TrafficSignalController* component manages how long each signal stays within its respective state (see Appendix B, Table B2).

A stand-in is substituted into the IGE as an 'ego-agent', designed to represent the real human user-participant in the simulation run-time. The ego-agent is *directly* controlled by the real motion, locomotion, and movement of the human-participant in the studio space. In animation, we rendered a yellow dot that follows underneath the player's head position and acts as a visible (but unobstrusive) indicator of where a participant's ego-agent is positioned relative to the IGE sidewalk and road. We made this design decision after initial prototyping showed that if we used full-body avatars, participants spent a lot of time in trials trying to jump and twirl their avatar (like a puppet). This is not



(a) Birds-eye view of the VGE model of a suburban American streetscape

(b) All VGE elements are geo-referenced to the streetscape scene

(c) Sidewalk, crossing, buildings, trees

(d) Ambient pedestrians waiting to cross

(e) Vehicles in the road and crossing

(f) Pedestrian group in the PELICAN crossing

Figure 3. Built geography of the IGE provides spatial substrate for modeled entities and the user-participant.

realistic in the real-world and proved counterproductive to our experiments. By providing users with a simple referential dot in run-time, participants in the experiments acted with authentic physical response to the IGE. In-system, however, we did represent the user as an avatar-based geometric mesh for the purposes of collision detection and distance calculations. This enables (physical) collision events to occur between the ego-agent and vehicles on the road. No collision interactions were implemented between the ego-agent and agent-pedestrians, so that we could *isolate movement behavior from user-participants to crossing alone*. (Online (real-time) collision detection between simulated agents and live user-controlled ego-agents is demonstrated in Torrens and Gu (2021).).

To enable georeferencing across both the virtual and tangible environments (via spatial and temporal position, and rotation tracking), four *HTC Base Stations* were set up on tripods around the studio and arranged so that the HMD was always in sight of at least one Base Station Figure 4(c). The real space and IGE space were mapped (dynamically) with 1:1 parity using (1) lighthouse georeferencing to the HMD VR for position and velocity, and (2) IMUs (a gyroscope for angular motion and G-sensor for acceleration). To drive the IGE as a run-time VR/VGE, we implemented a version of our model for *Unity3D*. This was passed (dynamically) to a HMD using *Unity*'s *OpenXR* and *XR Interactions Toolkit* (which allows extensions to a wide array of VR HMDs). We used a *HTC Vive Pro* with a visible field-of-view (FOV) of 98° horizontally and 98° vertically with a resolution of 1440 × 1600 pixels/eye. The simulation was transmitted to the *HTC Vive Pro* at a near-constant frame rate of 90 Hz with *SteamVR* as the runtime environment and we used a *Vive Wireless Adaptor* to enable wireless data transfer between the HMD and *Unity3D* engine. The wireless implementation also enabled untethered free range of gaze and locomotion.

Vehicle (and driver) model

We additionally represented roadside dynamics of vehicles at small geography in the IGE. To specifically produce simulated drivers, we used a modified Intelligent Driver Model (IDM) (Kesting, Treiber, and Helbing 2010; Treiber, Hennecke, and Helbing 2000) to operate within a geosimulation framework as a Geographic Automata System (GAS) (Benenson and Torrens 2003, 2005; Torrens 2004; Torrens and Benenson 2005). The GAS was programmed to animate within an IGE (Batty et al. 2001; Lin et al. 2015; Torrens 2015a; Torrens and Gu 2021) and we added realistic vehicle models, driving idiosynracies, wheel animations coupled to velocity, and engine noises coupled to velocity (Figure 5). Heuristically, our adaptation extends IDM to additionally permit interactions with objects beyond header vehicles and interweaves weighted randomization of vehicles' target velocities (Table B1).

We specified the original IDM as follows. For any i^{th}, vehicle on the IGE road, let $h(i)$ represent the i^{th} vehicle's leading vehicle. The acceleration of the i^{th} vehicle with respect to time t is defined as:

$$a_i(t) = a_{\max}\left[1 - \left(\frac{\upsilon_i(t)}{\upsilon_{t\,\arg}}\right)\delta\left(\frac{S_{opt}}{\Delta p}\right)^2\right] \tag{1}$$

Above, the hyperparameters (original to the IDM implementation) are:

- Δv: the difference in velocity between the i and $h(i)^{th}$vehicles.
- Δp: the headway distance (in time and space) between the front of the i and back bumper of the $h(i)^{th}$ vehicle.
- S_{opt}: the optimal headway distance between the i^{th} and $h(i)^{th}$ vehicles.
- v_{targ}: a constant velocity that each i vehicle targets and is capped at.

Except for v_{targ}, which is a constant value, these original hyperparameters only take interactions with the $h(i)^{th}$ vehicle into consideration. Therefore, we adapted the IDM to account for:

- S_{max}: A 'maximum distance' threshold parameter, unique to each i vehicle, that identifies if an obstacle in front of the i^{th} vehicle should be considered a header object or vehicle.
- δ_L: A Kronecker delta variable that observes an upcoming traffic light signal's status (Equation 2).
- δ_{ps}: A Kronecker delta variable that observes whether a header obstacle or vehicle exists based on S_{max} (Equation 3).
- p_l: The position of an upcoming traffic light signal in world space.

$$\delta_L = \begin{cases} 0 & \text{if single } = Go \\ 1 & \text{otherwise} \end{cases} \tag{2}$$

$$\delta_{PS} = \begin{cases} 0 & \text{if } \Delta p \; > S_{\max} \\ 1 & \text{otherwise} \end{cases} \tag{3}$$

We substituted these (additional) hyperparameters as modifications to the original IDM components Δv, Δ_p, and S_{opt}:

$$\Delta v = \delta_{PS}[v_i(t) - v_{h(i)}(t)] + (1 - \delta_{PS})[\delta_L(v_i(t))] \tag{4}$$

$$\begin{aligned}\Delta p = {} & \delta_{p\,s}\left[p_{h(i)} - p_i(t) - length_{h(i)}\right] \\ & + (1 - \delta_{p\,s})[\delta_L(p_l - p_i(t)) + (1 - \delta_L)(S_{\max})]\end{aligned} \tag{5}$$

(a) A user-participant in the tangible space of our experimental studio

(b) View from the user's HMD within the simulation trial

(c) Base stations B1-B4 positions with at least one with line-of-sight of the participant's *HTC Vive Pro* HMD and *Vive Wireless* (P). We placed a *HTC Vive Wireless* sensor (W) at one end of the room to enable complete line-of-sight with the HMD regardless of its current location

Figure 4. User-participants are transposed from a tangible physical environment into the IGE.

$$S_{opt} = [1 - (1 - \delta_L)(1 - \delta_{PS})][S_{min} + v_i(t)T_{pref}] + \frac{v_i(t)\Delta v}{2\sqrt{a_{\max}a_{pref}}} \tag{6}$$

These modifications allow us to incorporate hyper-local action into vehicle-driver dynamics (and 'underneath' IDM-produced traffic flows, jams, bottlenecks, etc.). This

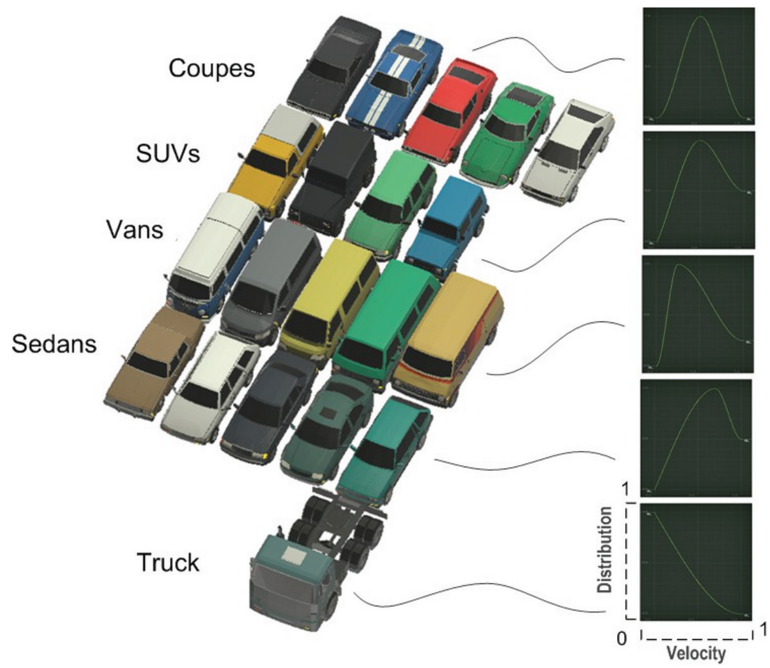


Figure 5. A variety of vehicle models are used in run-time, each with a distinct velocity distribution profile.

is important in establishing high-fidelity congruence to real traffic scenes at scales of the roadside edge. We can, for example, use the modified IDM within a GAS frame (all within the IGE) to (algorithmically) produce the small gaps in traffic that pedestrians necessarily consider when crossing. In particular, our modification to the fourth hyperparameter of the original IDM, v_{targ}, allows us to enable agent-based driver perspectives directly from local actions *in the road*. This provides support for generating impromptu ('emergent') traffic phenomena such as platoon formation, speed matching, bunching, and jamming behaviour at 'meso-scale' that then feed forward or back to 'macro-scale' phenomena such as non-equilibrium 'freezing by heating' effects known in dynamical and complex systems (Helbing, Farkas, and Vicsek 2000; Stanley 2000). In enabling this functionality, we open-up processes that fill significant gaps in the intervening geography of complex systems that we alluded to in the introduction to this paper. We also programmatically generated a unique v_{targ} value for each vehicle, using (weighted) specifics that draw from velocity distributions. Importantly, this means that we can represent very high-fidelity vehicle *capabilities* at 'micro-scale', indexed to vehicle class censuses (Figure 5), e.g. we are able to allow sedans to move more nimbly than trucks on the road. These fine details are then tied back to broader roadside rhythms and motifs (again, 'gap-filling' significant scale jumps in phenomena expression as geography).

The IDM is animated spatially and temporally in a given IGE scene, with its space-time geography provided by geosimulation. When a vehicle is spawned into the IGE, it is provided a starting point, a target destination, and (if in proximity to a crossing junction also) a traffic signal. (Our parameterization of the IDM for this is listed in Appendix B.) Based on the modified IDM model, the vehicle will move towards a parameterized destination target while checking for any vehicles that are ahead of the vehicle through *Unity*'s Physics.Raycast() method. In doing so, the vehicle will alter its acceleration based on local geographic information and its own driver criteria. If there is another vehicle within S_{max} in front of the vehicle, then the vehicle will attempt to match that vehicle's velocity and acceleration while maintaining a S_{min} gap distance. If there is no vehicle ahead but the traffic signal assigned to the vehicle has changed to 'red', the vehicle will attempt to decelerate to a stop in front of the crosswalk. Otherwise, the vehicle will move at v_{targ} towards its target destination and respawn upon reaching it.

To increase realism, vehicles are rendered with geometry models that match their vehicle census type (Figure 5). Vehicle wheels are animated to rotate based on the current speed of a vehicle. In simulation. each vehicle was designed to emit a sound effect that replicates engine noises that are unique to each vehicle subclass (trucks are louder than sedans; coupes rev with higher pitch than vans, etc.). Importantly, we mention that these sounds are spatialized, locally, to the current position of each vehicle. This also permits us to make use of the *HTC Vive* spatial audio functions within our HMD to create (geographic) senses of audio localization in the simulation. From a user-participant's perspective, then, this facilitates vehicle sounds to change in volume based on the user's current head position and orientation, increasing immersion for users and helping them identify the relative positions of incoming and outgoing cars.

Vehicles and simulated agent-pedestrians are programmed to never collide. System agents and vehicles have access to perfect information in the run-time GIS and geometry, so that they can plan for collision-free movement through the IGE. Agent-pedestrians can be programmed to interact with this information with probabilistic response (or even with error in judgement). However, unfettered access to geographic information is not the case for users, who must rather marshal their own information from the system as it presents in dynamic visual and audio form. Thus, vehicles may collide with users' ego-agent meshes (although their driving routine endeavours not to). If an IDM vehicle cannot avoid a collision with a user and the vehicle VehicleCollider comes into contact with the participant's UserCollider, the experiment run-time will produce a game-over scenario for participants. (The scene fades for the user and they are returned to the sidewalk inside a temporarily glowing blueberry jello-rendered envelope.) We introduced this procedure following evidence that users of road crossing VR may game the dynamics to investigate whether car would stop for them (Torrens and Gu 2023) (which is a risky proposition relative to reality, and which we discovered can dilute users' sense of fidelity of the system).

Pedestrian model

Our model pedestrians were implemented as GAS. One novelty of our approach is that agent-pedestrians consult a decision (state-transition) tree that is designed to route geographic information – which agents directly source from their localized and independent experiences in the run-time IGE – to transition functions between action states. Moreover, geographic information that agents consume is supplied to them from ambient state conditions on a relatively fast update schedule of 90 Hz. This has the result that the model agency appears as being 'real-time' in response to shifting conditions in the IGE. We aided this with knowledge discovery and data-mining (KDD) (in 2D for movement and distance look-ups) (Torrens, Li, and Griffin 2011; Zou et al. 2012) and slipstreaming (in 3D for collision, vision, and gaze look-ups) (Torrens 2015c). Substantively, agent-pedestrians operate with state transition rules that provide synthetic *individual* spatial behaviour, which we organized as a 'geo-tree' (i.e. a set of state transition pathways that branch and cycle to provide adaptive agency as response to encountered geographic conditions (Figure 6). Each agent retains its own independent geo-tree, with building blocks provided by:

Origin-destination path-planning: given a Scene, given a NavMesh: plan a movement Path along the sidewalk, populate a list(Waypoint), label each of the RoadsideWaypoint that intersect with the road-crossing and set them as a sub-destination with intervening goal.

Collision-detection: given a list(MovingPedestrians): calculate collision vector, identify a Collider.

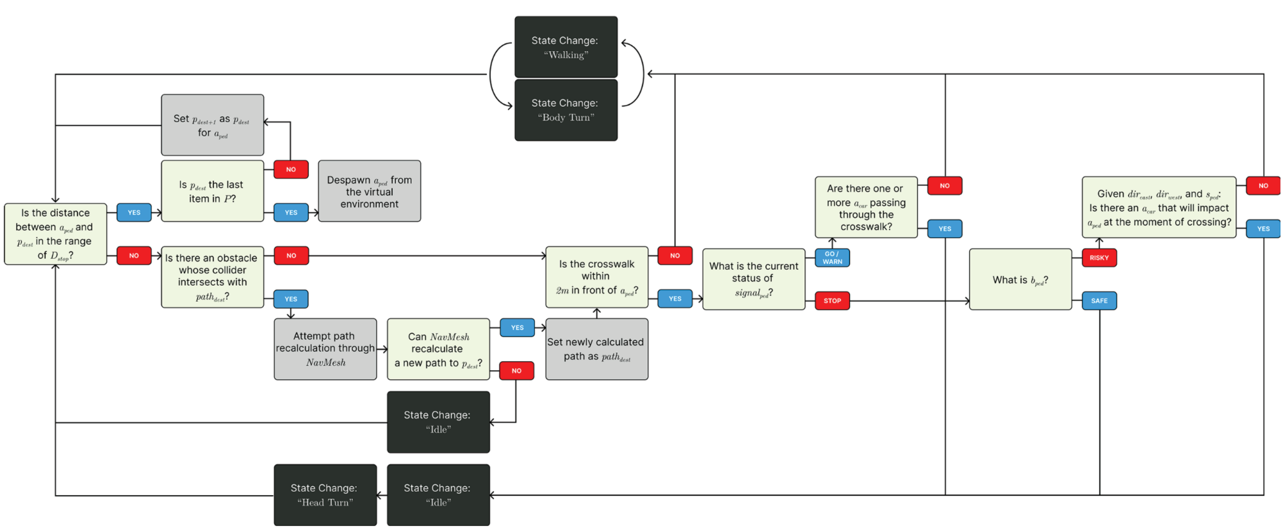


Figure 6. Geo-trees can be specified for all agents or individuals. In this example, the geo-tree starts from the leftmost box and flows rightward, leading into different states (black boxes).

Collision-avoidance: given a Collider: calculate an interim SubWaypoint to guide collision-free movement, steer to interim SubWaypoint, steer back to Path.

Signal observation: given a CrossingSignal: engage either of gap acceptance, halt movement, continue movement, or jaywalk.

Roadside scanning: given a list(NearbyVehicles), engage gap acceptance behavior.

Gap acceptance: given a list(MovingVehicles), given a list(NearbyVehicles): evaluate crossing safety.

Crossing: given a RoadsideWaypoint, given a GapAcceptanceThreshold, determine the beginning of a roadside crossing, the end of the crossing on the opposing side, invoke a decision to cross.

In the interests of brevity, we will not detail the specifications of the methods for building the above-mentioned pathways through a given geo-tree. Instead, we illustrate one example pathway in Figure 6 and we refer the user to the existing literature for GAS-based path-planning and trajectory management (Torrens, Li, and Griffin 2011), collision detection (Torrens 2014b), collision avoidance (Torrens 2014a), field-of-view look-ups (Torrens 2015b), gaze animation for gap acceptance (Torrens and Gu 2023), and locomotion (Torrens 2012).

We point out here that, as model-builder, one may alter underlying agent behaviour in a given geo-tree by straightforwardly manipulating the *tree elements* and their *connections*. In other words, fine-scale details of how to generate and compound geo-agency are managed, in the model, by manipulating *process representations* in the tree. Once specified, the geo-tree follows 'operator' programming-type schemes used in animation software (*surface operators* on objects, *dynamic operators* on solvers, *vector operators* on scene elements, *channel operators* on motion files, etc.). This also allows agents to pass the 'end' of one geo-tree to another agent, so that they can engage in reactive and process behaviour in a sequential fashion (Zeedyk and Kelly 2003).

We need agent behaviour to produce authentic geographic information that users will perceive and act upon with some level of authenticity in counterpart response. Key, in facilitating these part – counterpart dynamics, is building realistically functioning crossing decisions that allow agent-pedestrians to respond to individual vehicles, traffic gaps, signalized crossing opportunities, and jaywalking epochs. Moreover, agents' synthetic behaviours should match to users' perceptions of a given crossing scene and instance. To accommodate this, we designed agent-pedestrians with per-pedestrian, per-scenario *risk level* ('safe', 'risky'), *maximum speed*, and *delay time* prior to crossing. These parameters are specified as states and weights that work alongside GAS neighbourhood and movement rules (Torrens and Benenson 2005).

In 3D context, IGE objects provide an input stream of scene objects that are relevant to the *action locality* for a decision. For agent-pedestrians, the required IGE objects for spatial action (e.g. for determining spatial properties such as distance and angle) are provided by slipstreaming, e.g. by localizing navigation meshes, object-based occlusions, and neighbourhood proxemics between agents and the IGE) (Torrens 2015c). We note that slipstreaming can provide support for managing the three-dimensional geographic information (and time-vectored states) of spatial objects, against a variety of geographic contexts, including geometry, meshes, state-based parameter spaces, and so on.

To create coarse-scale pedestrian dynamics (beyond the immediacy of crossing decisions), we specified *compound pedestrian phenomena*. Importantly, we sourced these compounds in low-level behaviours, assembled together in different recipes of individual action and proaction. Taken together, the sum of individual decisions and compound behaviours was used to establish pedestrian motifs of roadside phenomena. Specifically, we reasoned that at a hyper-local scale around a given crossing, crowd behaviours (i.e. interacting groups of pedestrians) might influence user-participants' fleeting and opportunistic decisions, such as where on a sidewalk to attempt crossings (corner, mid-road, jaywalking), their decision to approach a given crossing or not, as well as their calculus regarding when to assemble at a crossing (e.g. to hold back if the roadside is crowded and they do not have a view) (Chrysler, Ahmad, and Schwarz 2015; Figueroa-Medina et al. 2023; Hess et al. 1999; W. Wang et al. 2011). We therefore introduced realistic pedestrian flow patterns to serve as visual and cluttered obstacles in participants' assessment of road-crossing conditions, and collective crowd pressure (Koilias, Mousas, and Anagnostopoulos 2020) and persuasion (Burgoon, Birk, and Pfau 1990; Mehrabian and Williams 1969) for different densities of crowd movement and pre-crossing assembly. We handled these using A* path-planning to route single agent-pedestrians heuristically to crossing sites (P. E. Hart, Nilsson, and Raphael 1968) with local steering for intervening collisions handled as Reciprocal Velocity Obstacles (van den Berg, Lin, and Manocha 2008). As demonstrated by Torrens et al. (2012), in aggregate, this is enough to produce adaptive lane formation in pedestrian sidewalk traffic and bunching at the roadside (although crowd behaviour in real-world settings is likely reactive/interactive, and not actually heuristic). These dynamics could conceivably be expanded to include other dyad, group, crowd, and social behaviours straightforwardly within the local action framework, particularly by geosimulation-based methods (Torrens 2016a, 2018b, 2022a, 2022b, 2023; Torrens and Griffin 2013; Torrens et al. 2012).

In modelling pedestrian agency, we considered how to establish realistic-seeming threshold behaviour (Granovetter and Soong 1983; Sueur et al. 2013) from ambient geographic information, i.e. the proclivity of user-participants to cross roads under the prompting and influence of ambient impulses to action that they perceived in their social surroundings. To drive this effect in the IGE, we introduced pedestrians with a variety of appearances, which were designed for potential peer (Tabibi and Pfeffer 2003) and authority effects (Torrens and McDaniel 2013). We also programmed conditions for *crossing groups*, as pelotons of pedestrians moving in (uncoordinated and often fleeting) unison. These mobile and trajectory-based dynamics provide an additional axis of examination for threshold effects, particularly as they might play out in group movement (Gorrini, Bandini, and Sarvi 2014), through following-type phenomena (Nara and Torrens 2007), and proxemics-related (Cook 1970; Hall 1963) issues of how crossers buffer personal distance in hurried movement (Rio, Dachner, and Warren 2018).

Appearance, in particular, plays an important role in peer effects at the roadside (Pfeffer and Hunter 2013) and can form the basis for threshold behaviour in group and crowd settings (Granovetter and Soong 1983). Each agent-pedestrian was instantiated with a customized mesh to reflect appearance characteristics along two axes of differentiation (Figure 7). Characters were randomly assigned facial appearances and given accessories such as headphones, face masks, or glasses.

Underneath agents' appearances, we coupled a specific geo-tree to work in concert with the IGE's animation engine (which we built within *Unity*). The geo-tree drives (1) the position of the pedestrian in the scene, (2) a space-time vector state indicating locomotion performance and required timing for state-shifts, and (3) head-turning commensurate with the location of an agent-pedestrian's visual attention see Figure 8(c,d). We note that agent-pedestrians are *fully-rigged* in the IGE system, i.e. they have synthetic skeletal structures that we can animate relative to a centre-of-gravity node that is tied to the vectors produced by the GAS (see the skeletal nodes in Figure 8(c)). With rigs, we were able to then generate realistic animated motions and locomotion to match the GAS space-time bundle for action. We relied on motion blending (Kovar and Gleicher 2003) to accomplish this (via *Unity* 's *Mecanim Animation System* in run-time atop existing motion capture libraries), with the blends controlled by transitions between each agent-pedestrians' current state in the geo-tree (Figure 6). In essence, agent-pedestrians thus produce realistic 'body language' that matches their motion (some examples are displayed in Figure 8).

Our intent was to invoke more than straightforward animation. We regard the visual run-time instances for agent-pedestrians' behaviour (output by the geo-tree

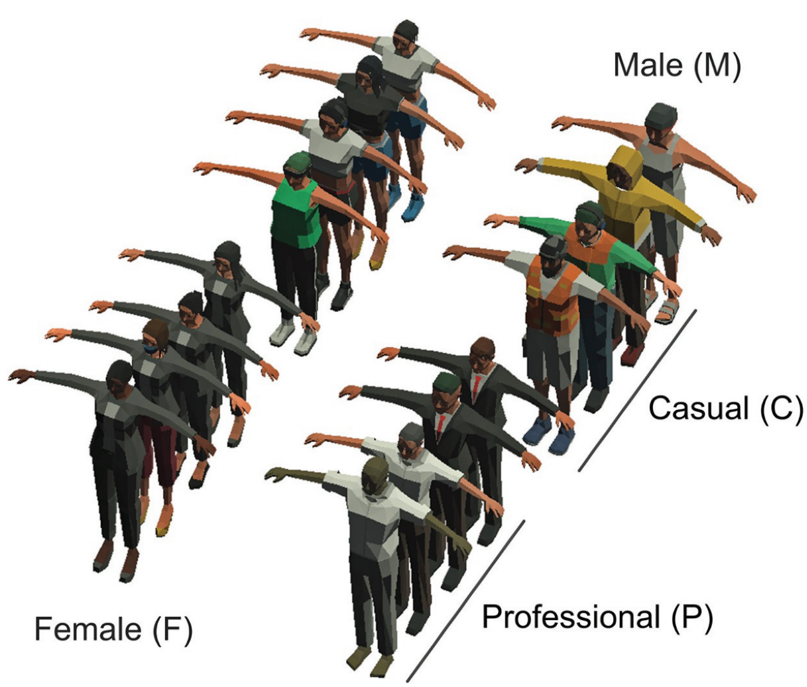


Figure 7. A variety of pedestrian appearances are used in run-time.

(3) attentive gaze (Geruschat *et al.* 2003).

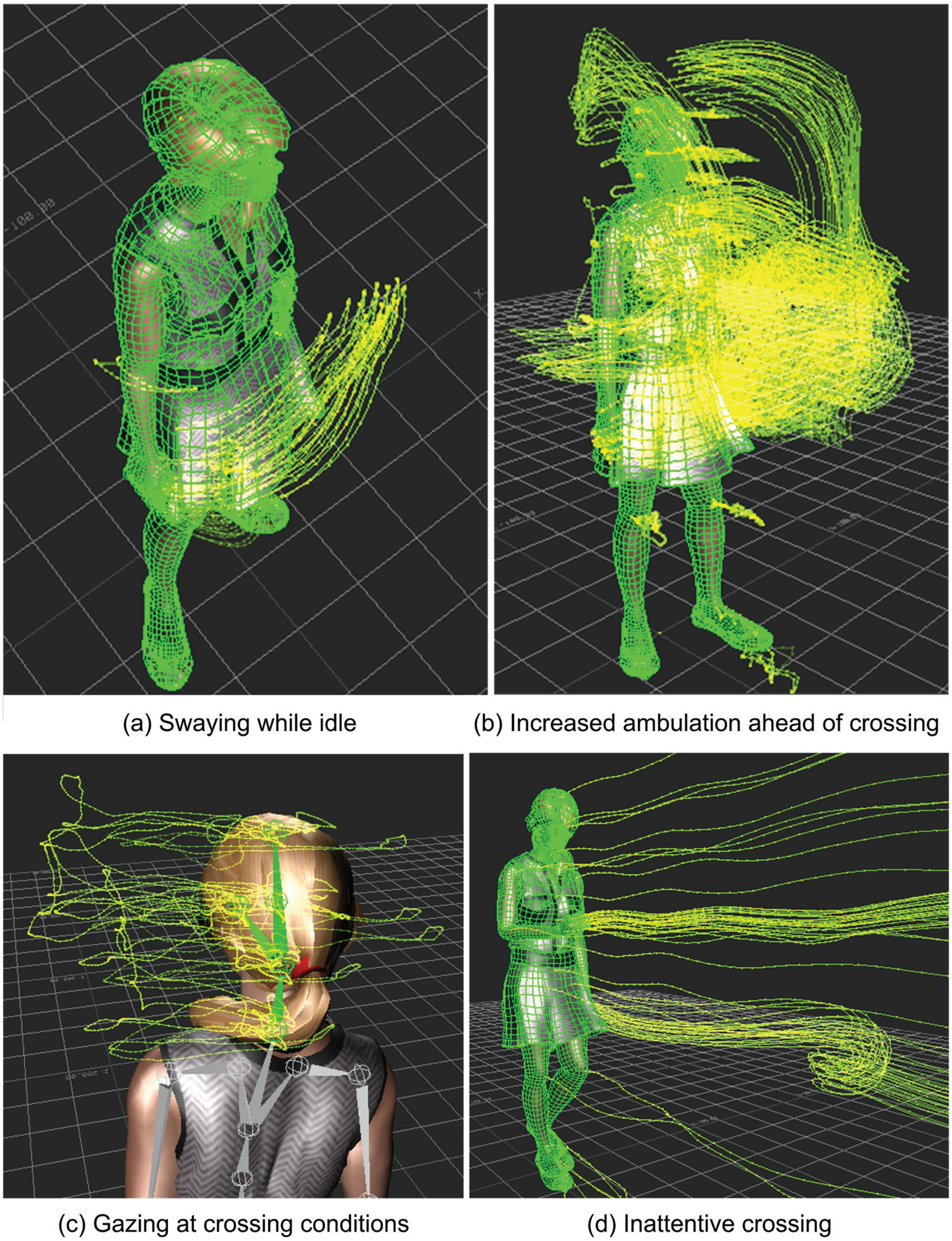


Figure 8. Pedestrian characters are endowed with body-language and mannerisms that yield cues of locomotion and non-verbal communications indicative of underlying decision-making: both may be interpreted, visually, by user-participants during experiment run-time.

dynamically) as important because they provide for three essential (dyadic) visual signs of agency that users would encounter in real-world pedestrians: (1) mannerisms to indicate dyadic interaction (Chu and Kita 2011), (2) space-time signals from locomotion and non-verbal communications (NVCs) from gesturing (Hariyono and Jo 2017), and (3) attentive gaze (Geruschat, Hassan, and Turano 2003).

User-participant experiments in a roadside immersive geosimulation environment

The intent of our study was to explore the propensity for IGEs to facilitate embodied spatial behaviour in virtual geographies. The geosimulation-driven local action models that we described above should facilitate this in methodology. But, we still need to prove that the system can do this efficiently and effectively in practice with real human test subjects involved in real test scenarios. We approached this issue by establishing a set of user-participant trials with 36 varying road-crossing scenarios. We recruited 24 participants (nine female, fifteen male) by snowball sampling. (In what follows we report on 22 of the cohort due to complications in survey collection.) Recruitment and informed user-participation was approved by the *Institutional Review Board* at our home institution. We note that the study ultimately involved a total of $22 \times 36(792)$ run-time experiments over several weeks of participation with human users. The experimental trials were varied across four main axes of roadside and crossing scenarios:

- Number of agent-pedestrians crossing the street with the ego-agent;
- Visual appearance of agent-pedestrians (professional, casual, mixture);
- Demographic of agent-pedestrians (male, female, mixed cohorts of each);
- Risk behaviour of agent-pedestrians ('safe', 'risky', mixture).

For ease in interpreting results, we kept the IGE model of the built roadside environment stable through each scenario for each trial. Participants were invited to cross to the other side of the road within the IGE and to do so as they would in the real world. As participants engaged with the simulation, we recorded empirical metrics using a set of data listeners (Torrens and Gu 2021) operating at 0.05 second intervals (approximately every 4 frames). The listeners were specifically trained on raw (machine-generated) data from the system hardware. Specifically, we streamed the position and rotation of the **participant's HMD** in the studio space. From the geosimulation run-time, we then streamed (by companion) the position, rotation, linear velocity, and angular velocity of **all vehicles and agent-pedestrians** in the IGE. Alongside machine data, we programmed a further set of *in-simulation* listeners to dynamically deliver substantive signals and motifs of road-crossing behaviour. We collected information on **completion** as the time to accomplish each trial task. **Crossing success** was used to tally both agent-pedestrians' and individual participant's attempts to complete a crossing. Attempts were labelled as either being successful or not successful based on whether the participant had (1) moved into the road or crosswalk but returned to the starting sidewalk (an aborted attempt), (2) collided with a vehicle (a failed attempt), or (3) whether the participant had managed to reach the other sidewalk (a successful attempt). **Gap acceptance** indexed the number of accepted and rejected traffic gaps for each participant. 'Naive' gaps were delineated as rejected gaps in traffic that present before the participant made a successful crossing, regardless of their time duration. 'Filtered' gaps are limited to those that are equal to or longer in duration than each participant's fastest attempt across all trials. This ensures that smaller, impossible gaps such as those between cars in platoons are not used in our follow-on statistical analysis. We collected data on **vehicle progression**, including timestamps of when each vehicle in the trial crossed the centre line of a crosswalk. The listeners also tracked **gaze**, with distinctions between filtered and aggregated gaze fixation counts across each gaze target type (agent-pedestrians, vehicles, crossing signals, traffic lights). These gaze data were built by ray-tracing from participants' ego-agents to each (and every) object in the IGE run-time. We aggregated gaze fixation points from all participants across all trials as **holistic gaze maps**.

We also exported complete video and audio run-time records of the IGE for each participant-trial, including the **individual viewsheds** that each user experienced in the HMD with matching video of their **physical movement actions** in the physical studio space. In total, this amounted to almost six hours of data (parsed at a resolution of 0.05 seconds, or 420,000 snapshots), which is geo-referenced to both the physical studio space and to the virtual space within the IGE.

Scanning the data that the system outputs can only tell us so much (particularly if one considers that we also designed the system, so there is potential path-dependence in what we look for). To build more insight beyond the streams that we receive from the data listeners, we collected a series of mutually-reinforcing qualitative data points about the trials. We assembled these data directly from user questioning and interviews with participants. Ahead of the experiments, we conducted an online questionnaire survey of participants' demographics (age, sex), driving experience, and pedestrian and vehicle accident history. We used semi-structured exit interviews to follow-up on the survey and questionnaire responses and the explanatory signals that those data provided. We note that the surveys were carried out electronically so that results were available during follow-on interviews after the questionnaires were completed. (The complete question set is listed in Appendix A.) These exit data were intended to buttress the data streamed during the run-time of their participation. The post-trial questionnaires posed Likert response questions to several facets of reality in the system:

- **Presence (P)** questions – We probed participants' feeling of 'being there' by deploying the *iGroup Presence Questionnaire (IPQ)* (Schubert, Friedmann, and Regenbrecht 2001).
- **Plausibility (R)** questions – We used a custom questionnarire to engage participants regarding their trust and confidence that the IGE depicts objects, characters, events, behaviours, processes, and phenomena that match users' own experiences in the real world.
- **Performance (T)** questions – We modified the National Aeronautics and Space Administration (NASA) *Task Load Index* (S. G. Hart and Staveland 1988) to gauge users' task burden as frustration, mental stress, physical stress, and discomfort during the trials.

To assess the role of *crossing context* in the IGE trial scenarios, we also asked participants to Likert-weight (1) the influence of encountered crossing attributes on their behaviour within the IGE trials; as well as (2) their recollection of how the same factors influence their everyday crossing behaviour in the real world. The questions were based on an aggregated list of 38 factors by Rasouli and Tsotsos (2020) that are commonly factored into studies of real-world urban crossing decisions.

Results

Given the amount of interaction and event data that we are able to harness through IGE experimentation, there are many possible axes for interpretation of results. Here, we focus on (1) participants' (qualitative) stated responses to their experiences in the simulated road-crossing trials; (2) revealed (quantitative) behavioural responses to system events in the experiment crossing trials; and (3) analytical results (computed) of participant-model interactions in simulation run-time. For **P**-, **R**-, and **T**-questions (see Appendix A), aggregate results are reported in Appendix C (Table C1). These results are shown in decomposed form in Appendix E (Figures E(1-3)). Additionally, we report results of real/virtual event influences of user-participants in Appendix D (Figures D(1-3)).

Participant survey results

Generally, user-participants responded to the IGE as being pragmatic in evoking their naturalistic spatial behaviours. The presence surveys indicated that participants felt that the IGE supported their natural ability to perceive the space around them (questions **P3**, **P4**, **P6**, and **P7**; readers may wish to consult the detailed results in Table C1). The generally neutral response to **P11** ('To what extent were you able to distinguish the virtual environment from the real world'), with supporting evidence from our follow-on interviews, indicates that users (unsurprisingly) were aware that the simulation was never really 'real' (to begin with), but nonetheless could suspend disbelief that they were in a simulation at least while engaging in moment-to-moment dynamics of the experiments.

The plausibility responses were positive-leaning for queries **R1**, **R2**, and **R3**. This indicates that users felt compelled by the IGE to behave as they would in real-world road-crossing, as in well as real-world collision (avoidance) scenarios. This is important insight, suggesting that participants' behaviours against *dynamic road-crossing stimuli* (i.e. vehicles and pedestrians) were realistic. However, *backdrop stimuli* (i.e. the built environment and fixed crossing signals and traffic lights) produced more varied response. This is an intriguing result, as it emphasizes user's reaction to free-flowing space-time dynamics in IGEs, even amid the presence of stagnant landmark-type objects (lamp posts, zebra crossing, curb edges, etc.).

Likert scores for questions related to task load (**T**-questions) were generally low, indicating that participants felt that the IGE did not place unrealistic spatial performance demands on them. However, we did note some task-load issues relating to field of view (FOV). Occasional high scores for question **T1** correlated with participants who noted that the limited FOV of the HMD made it harder to see things in the periphery of users' vision. Our follow-on interviews indicated that the innate nature of HMDs in constraining peripheral vision contributed to other responses in this category as well, with participants noting that the artificially (slightly constrained) peripheral vision that HMDs impose lead to them committing the relative positions of approaching vehicles to short-term memory. In essence, we think, participants had to devote unrealistic time to memorizing vectors of moving objects because they disappeared from peripheral vision sooner than they anticipated. However, participants were able to adapt to the HMD FOV as trials continued on in their respective scenarios.

Statistical analysis of event data and event experiences

Because we had access to participants' own self-reflections on virtual and real influences, we performed statistical testing to examine whether the IGE had produced a statistical shift (from real to virtual, i.e. from real2sim) in relative influence of participants' (self-perceived) crossing behaviour. We gathered data for this evaluation by asking respondents to Likert-rate the usual influence of crossing factors and crossing events on their realworld behaviour. We then asked the same questions for their experiences in the IGE trials. We established a Paired T-Test with a p-value threshold of $\alpha = 0.05$ on an initial null hypothesis h_0 that the IGE would *not* produce any differences in responses towards road-crossing influences. Detailed results are presented in Table C3.

We performed further statistical analysis of streamed event data from the trials to evaluate user engagement in specific simulation phenomena, using the Shapiro-Wilk Normality Test (SWT) and Kolmogorov–Smirnov Test (KST) to control for participant attributes from the pre-trial questionnaire. (Detailed results are presented in Appendix C, Table C2.) Per-trial durations, rejected gaps (naive), and number of rejected gaps (filtered) were found to be parametric according to the normality assumption and required either the Independent T-Test (for sex and licence ownership) or One-Way ANOVA (for age group, prior witnessing of pedestrian accidents, and prior involvement in pedestrian accidents). Alternatively, the metrics for number of red-light violations, number of rejected crossing attempts, and number of vehicle collisions were regarded as non-parametric and required either the Mann-Whitney U Test (for the sex attribute and for licence ownership) and Kruskal–Wallis One-Way Test for Variance (for age group, prior witnessing of pedestrian accidents, and prior involvement in pedestrian accidents) (see Appendix F).

Table C4 and Figure F1 show the results of significance testing of run-time events across different participant demographic factors. With $\alpha = 0.10$ as the p-value threshold for comparing different factors among the same population, we found significance in the effect of *participant sex* on the number of red light violations ($p = 0.041$) and trial duration ($p = 0.098$) in the experiment trials. Male participants tended to commit more red-light violations than female participants did, and males experienced greater numbers and variations in failed attempts at crossing. This correlated with higher numbers of collisions with vehicles. Females generally took longer to complete trials, whereas males' time-to-completion skewed heavily towards shorter crossing times (i.e. they were more hurried). While the overall number of rejected gaps is similar across demographics, males rejected more opportunities to cross when they feasibly could, given each participant's fastest time-to-cross. These findings match the current theoretical understanding of real-world road-crossing behaviour in the safety science literature, which shows generally riskier behaviour of males, especially young men (Onelcin and Alver 2015). Indeed, we found that participants from younger *age groups* in our study tended to perform more red-light violations than their older counterparts did, and that they experienced more failed crossing attempts (Figure F2). No discernible trends in time-to-completion duration or number of rejected gaps were found to be statistically relevant.

We found broad correlation between participants' backgrounds and their behaviour in the IGE trials (Figure F3). *License ownership* had a statistically significant effect on trial duration ($p = 0.071$). Whether someone was *involved in a pedestrian-related accident* had a statistically significant effect on number of vehicle collisions ($p = 0.018$). Whether someone had *witnessed a pedestrian-related accident* had a statistically significant effect on both the number of red-light violations ($p = 0.031$) and the number of vehicle collisions that they generated in the simulation ($p = 0.035$).

(Computational) analysis of gaze dynamics

Road-crossing involves significant use of perception and cognition (Harrell 1991), and so we paid particular

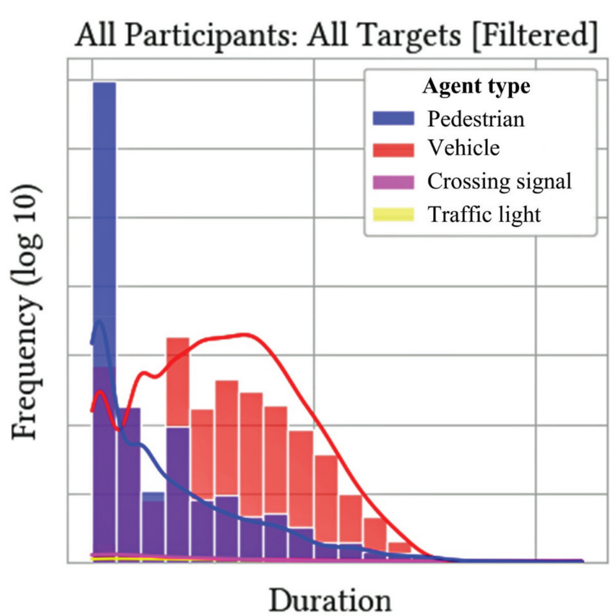


Figure 9. Gaze frequency and kernel density estimation curve by gaze object type.

attention to users' gaze behaviour in the IGE. Whereas similar techniques have examined how immersed IGE users focus their attention on static features of the built environment (Torrens 2023; Torrens and Gu 2021), our ray-tracing measures additionally focused on how participants observed dynamically simulated objects, and specifically which *parts* of those objects drew their attention. We display illustrations of the duration of gaze relative to each feature of the simulation in Figure 9. (Gaze fixations that only last a single frame are removed from the illustration.) Our results show a distinct gaze preference among participants in attention to agents, vehicles, crossing signals, and traffic lights. In other words, participants' attentional focus appears to have been on the dynamic elements of the IGE. It seems that participants may be using fixed features of the IGE environment for navigation, wayfinding, and movement (as is already known in VGE studies and in VR research of the built environment), but we found that participants' *ongoing and moment-to-moment attention* is trained on dynamic entities in the scenarios. In particular, histograms of gaze duration across all participant-trials reveal that participants cast their gaze most frequently at counterpart pedestrians, but for relatively fleeting snapshots of time. By comparison, participants' gaze upon vehicles was relatively longer in duration. Crossing and traffic signals received comparatively less attention. In other words, participants paid the most heed (relatively) to cars when crossing, which is perhaps as it should be when crossing the road.

Both of our analyses of gaze dynamics, as well as survey responses to the plausibility question **R3** (regarding participant-pedestrian collisions) indicated that participants used counterpart agent-pedestrians in their decision-making within the crossing trials. We reasoned that many factors could be at play here, including individual users' (perhaps peer) affect (Pfeffer and Hunter 2013) relative to characters or their personal tolerance for collision (Basili et al. 2013; Caird and Hancock 1994; Collett and Marsh 1974; Cutting, Vishton, and Braren 1995). It is also possible that this result is a factor of users' tolerance for *virtual* collisions more generally (Gerin-Lajoie et al. 2008).

To investigate this further, we built heat maps during 'crucial decision moments' (CDMs) prior to crossing. Specifically, we interpreted CDMs as small windows of space and time that a participant has to begin a first (initial) crossing attempt at the roadside. We generated CDM heat maps by combing the simulation geometry for (ray-traced) gaze fixation points of all participants. This generated a huge amount of gaze data, which we filtered to a sub-set of only gaze targets during CDMs. The resulting heat maps for the eight most prominently-observed agent-pedestrians are shown in Figure 10. The most salient areas of agent-pedestrians that participants appeared to fixate on were pedestrians' back, rear head, and rear neck areas. This follows evidence from observational literature on general pedestrian movement, which found that walkers rely on information from other pedestrians' backs as an indicator of future conditions that they may encounter head, i.e. gaze transfer (Gallup, Chong, and Couzin 2012). Critically, as we will shortly argue, we reason that users rely upon the geographic information that they acquire in CDMs to develop 'action maps' that dictate what they will do with that information in the next few moments of their spatial behaviour.

Findings

Our results point to four overarching findings. First, the IGE was able to evoke realistic spatial behaviours from

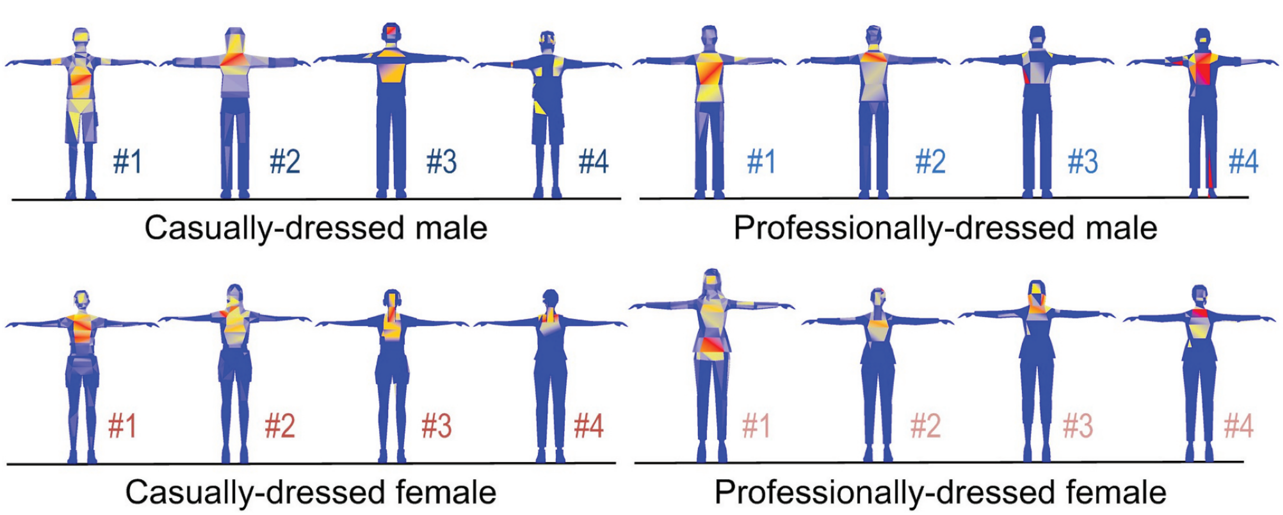


Figure 10. Heatmaps of participants' (collective) gaze fixation on the *back* of counterpart agent-pedestrians. Gaze fixation is color-ramped from blue (less interest from user-participants, through yellow and to red (most relative gaze fixation).

users. This suggests a robust utility in relying on IGEs as test beds for real-world experimentation. The remaining findings suggest *why* the IGE 'worked' and they point to the significance of functional fidelity and embodiment in fostering user credence of IGE's virtual geography as a plausible milieu for enacting spatial behaviour. Our second finding is therefore that IGEs can facilitate realism specifically by providing high-fidelity matches to real-world objects and phenomena, but crucially also that fidelity of function is at play with larger import than visual fidelity might have. Third, we found that users' sense of verisimilitude is tightly coupled to context, particularly to situational and presence-based context that localizes participants' behaviour to the right place, right time, right people, and in the right ways. In particular, this context seems to be drawn from dynamic facets of the IGE, which users localize to small windows of individually meaningful action in their attention. Fourth, we consider that fidelity of function and verisimilitude of experience go hand-in-hand during users' interactions with the IGE through the mechanism of embodiment; but to invoke users' behaviour, embodiment must survive users' exploration and interrogation of its authenticity.

Realism in behavior by demographics and background

Proving that IGEs can actually entice realistic behaviours from participants is an important test for the validity of the approach. Without meaningfully realistic response behaviours from users, the system would otherwise be hobbled in its ability to support substantive research on road-crossing. One of the key signals of variation in road crossing behaviour (particularly safe and unsafe behaviour) in the literature is sourced in demographic differences of crossers (Oxley et al. 2005). For the most part, our experimental trials reproduced these known demographic factors.

The sex of participants had a statistically significant effect on risk-taking in the IGE trials, e.g. willingness to violate red lights and hurrying through the crossing trials. This echoes existing case study findings for real-world crossing (Hamed 2001; Rosenbloom 2009). Our IGE experiments also reproduced high-resolution crossing differences in sex. For example, that females display greater levels of caution when crossing under risky conditions (Heimstra, Nichols, and Martin 1969; Holland and Hill 2007; Moore 1953; Yagil 2000).

Given the potential impacts of road-crossing safety on vulnerable populations, a huge amount of existing literature can be found to tease out age-related factors in crossing behaviour (Harrell 1991; Langlois et al. 1997; Liu and Tung 2014; Lobjois and Cavallo 2009; Oxley et al. 2005; Pfeffer and Hunter 2013; Zeedyk, Wallace, and Spry 2002). Due to constraints in our institutional review board human subjects protocol, our experiments lacked recruitment access to children and senior participants. Nevertheless, we do have a few points of comparison with existing case study literature, particularly work by Mirzaei-Alavijeh et al. (2019), whose participant pool also featured adults between the ages of 19 to 30.

Prior research (Hamed 2001) highlights that those who have experienced road crossing accidents tend to demonstrate more caution in their behaviour at the roadside, especially as measured by longer waiting times prior to crossing. Our IGE experiments were able to reproduce these effects.

Realism from fidelity

We found that users interpreted the IGE as faithfully representing road-crossing environments, events, and phenomena. Below, we consider these findings specifically for the environment's built geography, vehicles, and pedestrians.

We found that users correctly interpreted the **urban geography** of the (static) VGE, quickly becoming accustomed to their place in the larger downtown setting, localizing waypoints to move towards (Tabibi and Pfeffer 2003), and correctly planning interim goals as parts of paths through the built setting. Participants also showed realistic appreciation for hyper-local geography of the roadside, correctly identifying and stopping at curbs, and entering crossing decisions at signalized crosswalks, while also passing through PELICAN and zebra crossing zones within the IGE during signalized opportunities. Similarly, when moving to unsafe areas of the IGE (by jaywalking), participants were impetuous in their decision-making and hasty in their traversal of those areas, as they would be in real roadside geographies.

Importantly, we found that users were adept at polling localization references from the IGE with a high degree of geographic accuracy. In particular, participants were successful in judging distances, as well as time geography of dynamic elements (chiefly other pedestrians, vehicles, traffic lights, and crossing signals). Again, we highlight the broad evidence from our trials, showing that participants made particularly broad use of dynamically-shifting **spatiotemporal** information to drive their behaviour in the IGE. In this way, then, we see useful interplay between the dynamics of the geosimulation and the statics of the VGE.

Participants felt that **vehicles and traffic dynamics** provided usefully faithful representation of their real-world counterparts. We attributed this to be an effect of *functional fidelity*. For example, when interviewed, participants cited the varying velocities of cars as realistic because the vehicles did realistic (space-time) things in the IGE. This functional fidelity assisted participants' behaviour by informing their localized action. In particular, participants reported that vehicles' wheels (which were animated to rotate relative to velocity) provided an actionable cue for their behaviour (tipping them off to vehicle speed and acceleration, and therefore informing their estimates of the future space-time gap they could accept in traffic). However, several participants bemoaned the fidelity of deceleration for vehicles in the simulation. In our study city, speed limits are constrained to 25 miles per hour on most streets, with the result that real vehicles tend to slow down (rather than halting) in a sort of slow crawl manoeuvre around pedestrians that also takes leeway with permissive red light turning rules. This suggests that some vernacular fidelity effects may be at play in affecting how users regard functional fidelity, or its authenticity relative to local customs or norms.

We also identified support for the prominence of functional fidelity in shaping users' realism of experience with **agent-pedestrians** in the IGE. We were not, however, entirely successful in delivering an empirical explanation as to why. For example, some users cited that the agent-pedestrians moved realistically and even referred to the way agent-pedestrians rotated their heads to look at approaching vehicles as being convincing of the agents' behaviour. Other participants found fidelity in agent-pedestrians' social credentials. For example, a participant attributed agent-pedestrian head-turning to a supposed 'judgemental' reaction from the agent-pedestrians, reasoning that agents were looking at the participant with some level of disapproval of their attempt to cross the street before the crossing signal indicated a safe crossing opportunity. This is an interesting finding as it indicates the strength of rather simple gesturing behaviour of our agents in producing a quite distinctly recalled reaction of social peer pressure and norm expectations.

However, other participants doubted the fidelity of agent-pedestrians' spatial skills. Interestingly, some users mentioned that agent-pedestrians' ability to precisely engage small-lived traffic gaps while jaywalking exceeded realism. The question of how users relate to agent-pedestrians therefore requires much more investigation. Elsewhere, we have examined inter-personal effects of spatial behaviour using measures of affect by coded observation relative to indoor settings (Griffin et al. 2007; Torrens and Griffin 2013). The same technique may be useful here, but would require extension to factor the open nature of outdoor settings, as well as dual manual coding across video footage of the room and in-simulation footage from users' HMDs.

Realism from verisimilitude

Critically, for the IGE experiments to be useful in informing domain science involving human subjects, one should expect users of IGE to feel that their own actions have realistic import in the virtual setting. Overall, the high presence scores that we reported for our experiments indicated that participants did feel that the IGE was sufficiently verisimilar to real road-crossing experiences. We found this across several dimensions of verisimilitude.

Our findings point to factors **beyond visual immersion** as being important in driving participants' sense of verisimilitude, but only up to a particular level of visual resolution. In a somewhat counter-intuitive finding, most participants associated a keen sense of presence to the low-polygon/low-resolution visual depiction of the virtual environment and characters. This matches evidence from studies of the 'uncanny valley' (Mori, MacDorman, and Kageki 2012) effect in robotics. The concept posits that humans develop affect and other natural regard for humanoids up to a point somewhere between abstract representation and hyper-realism (i.e. the 'valley' between them). But, as humanoids' visual appearance approaches realism, people begin to recoil in maintaining natural behavioural relationships with those synthetic visual representations. However, we do wish to point out that we did not vary the visual resolution of our system across trials. So, we cannot directly gauge the relative verisimilitude of low polygon and high polygon visuals. This is a topic that we hope to pursue in future experiments.

We found that the actions of participants were realistically drawn out through participants' sense of connection and rapport to counterpart characters' **body language**. This was evident, particularly, in our gaze testing. This finding suggests, perhaps, that NVCs (Mehrabian 1968), which are relatively low in visual bandwidth (compared to high-resolution detail of human-like surface appearance), may be a key channel for person-to-person interaction at the roadside. We note, in particular, that NVCs convey geographic information, e.g. in the form of head-turning that signals objects and events that nearby agent-pedestrians find 'interesting' and therefore something that a participant might also want to pay attention to. This finding relates to evidence of gaze transfer among humans in mobile social groupings (Gallup, Chong, and Couzin 2012). We note, for example, that we also found repeated evidence that participants relied on space-time cues of action and locomotion expressed in agent-pedestrians' individual behaviour, which user-participants incorporated into their assessment of broader rhythms and motifs of crossing or gap-rejection.

We propose that counterpart mannerisms that include non-verbal cues may assist in participants' construction of **'action maps'**, as a sort of dynamic and interactive equivalent to mental maps. As we alluded to in Section 5.3, participants in the IGE trials acquired geographic information during fleeting windows of space and time, what we referred to as crucial decision moments. This is an idea that was explored by Torrens (2016b) in agent-based modelling, which introduced a way to conceptualize this (in spatial analysis) as 'behavior regions' in agents' mental maps. That proposition (tested only within computational agency) was that larger areas of urban geography (a few city blocks) that would traditionally be considered as accessible in pedestrian behaviour as broad-area mental maps might be usefully decomposed into behavioural sub-regions where time geography takes over as the dominant logic driving spatial behaviour. Here, in fact, we see a similar effect in real behaviour of users within an IGE. Specifically, participants put significant stock in the geographic information that they acquire during CDMs. We will need to investigate what, exactly, users call upon in their behavioural faculties to process CDM geographic information. We posit that one could consider that participants use action maps to build geographic information from the tapestry of rhythms and motifs that present in hyper-local envelopes of space and time around them. Specifically, that they may map those motifs to their own egoagency (their own local and pollable context) as action maps. Thus, we could consider a hierarchy of *mental map* → *behavior region* → *action map* ←→ *crucial decision moment*. Different pieces of geographic information might be useful at different scales or stages in this hierarchy.

We also found support for the influence of **auditory verisimilitude** in IGEs. Interestingly, sound was used in a distinctly spatial role to buttress users' embodiment in the geography of IGE trials. Participants remarked that engine sounds coming from the vehicles enabled their judgement of the relative positions and speeds of cars (i.e. by audio-localization to engine sounds). This in turn gave participants a better understanding of events happening around them and was crucial at moments when participants were focused on looking towards one direction of the street and were unsure if any cars were approaching from the other side. It is interesting to consider that sound, particularly for rule-based geographic entities (such as vehicles that should adhere to road rules and certainly abide by rules of physics), can be useful in providing human users with a preview of future geography. Specifically, sounds becomes integral in contextualizing visual geographic information, e.g. 'I am here and the things around me are there, but in a few seconds, the things around me will *move to there*'. Here, we highlight the multi-geographic information channels of the IGE as providing verisimilitude, specifically by allowing users to cross-reference localization across *overlapping geographies*, e.g. visual distance that is double-checked as auditory distance.

Pointing out that an IGE that was designed to enhance realism *was* actually realistic is semi-obvious. Explaining *why* is perhaps a broader topic for discussion and for exposition. Here, we advance the case for **embodiment** as the driving force behind congruence in the IGE concept. In particular, we found that functional fidelity plays a key role in establishing participant trust and buy-in to the geographic information that the IGE generates and displays to users. Concurrently, we found that users essentially map that fidelity to geographies of action context (what we previously termed as action maps) as a way to put (trusted) geographic information to use in settling their spatial behaviour among informational options. In this way, verisimilitude seems to be used to *qualify and interpret* fidelity-based signals. In other words, the checking and verification that people engage in when building ambient context – as an action map, as ambisonic geographic information, as spatially localized traffic gaps, from ego-perspectives, from allocentric judgement, polled from other people in one's FOV, etc. – may be at play in bringing (extrapolated) behavioural meaning to otherwise 'raw' geographic information.

What is the mechanism driving these pairings of geographic information to spatial behaviour? We reason that embodiment provides an interface between geographic information and behaviour by shaping (via trust and authenticity borne of functional fidelity) snap-judgement instances of sensing, which are then 'made sense of' (interpreted in ways that inform a given space-time decision or action), in hyper-local context, as action maps that users experience and *enact* through verisimilitude. We suggest that our results point to a microcosm of small geographies (e.g. small local environments of perception, small bouts of space-time action, small checks to space-time cognition) that underpin this within situational embodiment (Kiverstein 2012), social embodiment (Meier et al. 2012), embodied cognition (Lindblom 2015), and enacted embodiment (including social action) (Anderson 2003) (p. 92). Our IGE approach suggests that these sub-embodiments can be evaluated – empirically – in virtual settings, which opens-up a broad canvas of possible experimentation, including for what-if scenarios outside the scope of tangible inquiry.

Conclusions

In this paper, we explored the (empirical) nature and form of the reality gap in geosimulation. In particular, we examined the gap that presents between people's everyday geographic experiences at the roadside and simulations of model agency and phenomenon dynamics that are used to explain and to explore those experiences in computational and informational form. We built a new form of IGE and used it to test simulated road-crossing scenarios with real immersed and mobile human user involvement. We empirically measured the reality gap through a paired focus on congruential fidelity and congruential verisimilitude.

We tackled the objective of fidelity using geosimulation-driven local action models of vehicle/driver behaviour and of pedestrian behaviour, making use of a modified IDM and a new geo-tree approach to geosimulation respectively to do so. We approached experiential verisimilitude by using inverse augmentation to envelop participants in visually, auditorally, and kinectically immersive VR and geosimulation in ways that left them free to move, wander, gaze, and explore using their natural proclivities and interests and whole-body spatial skills. Together, we consider that geosimulation, VR, and VGEs can be used to deploy a new simulation medium, which we term as 'Immersive Geosimulation Environments'.

Our findings show that IGEs can present faithfully appreciated geographic entities, phenomena, and environments. At the same time, IGEs can be verisimilar to user experiences and expectations in ways that foster life-like experiences. The computational, data-rich, and sensing-saturated nature of IGEs also facilitates very deep and detailed experimental control over simulation scenarios. These new capabilities, although admittedly preliminary and experimental, could (we think) build new synergies between simulation-assisted theory-testing and experimentation and the newly-arriving streams of immersive data that are incoming from geographically-aware sensing systems. We approached this potential, in this paper, in only limited form by using motion capture and streaming location data from HMDs. Nonetheless, we posit that our proof of concept highlights new possibilities for GIS to establish novel and exciting mappings between real and user-driven spatial behaviour (motion, gaze, crossing actions) and geographic information sourced form the virtual and vicarious geography of VR and IGEs (counterpart dynamics of mobile entities and objects, information gleaned from spatial audio data, character NVCs).

Of course, IGEs need to be *actionably realistic relative to the phenomenon being studied* for those advantages to take on any scientific or normative value. Not all dynamic elements in our system were found to properly capture the same level of verisimilitude. This opens the broader question of where, specifically, geosimulation foundations should undergird VR and VGE assets. Likely orbiting these questions, there are issues about when geographic abstraction is useful and when high-fidelity detail may be needed (compare the approaches in Glander and Döllner (2009) to those in Torrens (2014a), for example). This is a topic for future research, which would benefit from analysis of other domain experiments, beyond road-crossing.

We also see some broad potential for behavioural geography to inform new lines of research inquiry into virtual embodiment based around haptics and force-aware VR (Zhang et al. 2022). In particular, the sorts of IGEs that we have shown here, if developed for force-awareness, could be very useful in assessing issues of spatial skill in road-crossing, e.g. around known observational linkages between gaze and balance control for elderly walkers at the curbside (Zettel et al. 2007). This is perhaps suggestive of broader potential synergy between IGEs and human geography. Indeed, both geosimulation and human geography, if pursued in concert, could do a lot more to supplement each other in inquiry, if they can be brought to parity of ideas and data exchange. The trick to achieving this, it would appear, is building models that real people can relate to with their natural geographic curiosities.

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Authors' contribution

Authors contributed equally to study design, experiments, analysis, and writing of the paper.

Human Subjects and Participant Consent

The experimental protocol for this work was approved by our institution's Institutional Review Board. User-participants in the experimental trials provided informed consent to participate in the experiments.

Data availability statement

Due to the involvement of individual users and video footage of their likenesses and voices, we are unable to share the experimental data

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Appendix A. Survey questions for presence (P), plausibility (R), and performance (T)

P1: In the computer-generated world I had a sense of being there.
P2: Somehow I felt that the virtual world surrounded me.
P3: I felt like I was just perceiving pictures.
P4: I did not feel present in the virtual space.
P5: I had a sense of acting in the virtual space, rather than operating something from outside.
P6: I was aware of the real world around me while navigating in the virtual world.
P7: I was focused towards trying to pay attention to the real-world environment.
P8: I was completely captivated by the virtual world.
P9: How real did the virtual world seem to you?
P10: How much did your experience in the virtual environment seem consistent with your real world experience?
P11: To what extent were you able to distinguish the virtual environment from the real world?
R1: I felt compelled to behave as I would in the real world when deciding whether to cross the road in the virtual world.
R2: I felt compelled to avoid collisions with vehicles on the road.
R3: I felt compelled to avoid collisions with other pedestrians.
R4: I felt compelled to obey traffic signals when crossing the road.
T1: Mental Demand On a scale between 1 (very low demand) and 7 (very high demand), how mentally demanding was the task?
T2: Physical Demand On a scale between 1 (very low demand) and 7 (very high demand), how physically demanding was the task?
T3: Temporal Demand On a scale between 1 (not rushed) and 7 (very rushed), how hurried or rushed did you feel was the pace of the task?
T4: Effort On a scale between 1 (no effort) and 7 (significant effort), how hard did you have to work to accomplish your level of performance?
T5: Frustration On a scale between 1 (not frustrated) and 7 (very frustrated), how insecure, discouraged, irritated, stressed, and/or annoyed were you?
T6: Success On a scale between 1 (unsuccessful) and 7 (successful), how successful were you in accomplishing what you were asked to do?

Appendix B. Local action model parameters for vehicles and traffic signal timing

Table B1. Vehicle parameters programmatically determined upon spawn.

Parameter	Description	Value
v_{args}	Max. vehicle speed	Weighted rand., 5 m/s to 15 m/s
S_{min}	Preferred min. desired distance to $h(i)$	Unweighted rand., 0.25 m to 0.75 m
S_{max}	Obstacle-ahead distance threshold	Constant, 6 m
T_{pref}	Desired advance time at current speed	Unweighted rand., 0.25s to 0.75s
a_{max}	Max. possible acceleration	Constant, $10m/s^2$

Table B2. Traffic signal states and timing.

Traffic Signal State	Pedestrian Signal State	Duration
'Go' (green)	'Stop' (hand icon)	30s
'Warn' (yellow)	'Stop' (hand icon)	3s
'Stop' (red)	'Go' (walk icon)	15s
'Stop' (red)	'Warn' (blinking hand icon)	30s

Appendix C. Statistical results

Table C1. 22-participant post-trial survey likert summary statistics.

Question	Sentiment	Mean	Median	Stand. Dev.
P1	Positive	5.6957	6.0	1.4855
P2	Positive	5.8696	6.0	1.3938
P3	Negative	1.9130	2.0	1.0375
P4	Negative	2.0435	2.0	1.2409
P5	Positive	6.0435	6.0	1.1719
P6	Negative	3.0	2.0	1.5937
P7	Negative	2.3478	2.0	1.7717
P8	Positive	6.0	6.0	0.9574
P9	Neutral	5.1304	5.0	1.4234
P10	Neutral	5.6957	6.0	1.1719
P11	Neutral	3.0435	3.0	2.1695
R1	Positive	5.9565	6.0	1.1719
R2	Positive	6.5652	7.0	1.0375
R3	Positive	5.0	6.0	1.8138
R4	Positive	3.2174	3.6087	1.9585
T1	Negative	3.4783	3.0	1.3838
T2	Negative	3.2174	3.0	1.3534
T3	Negative	2.5652	2.0	1.4136
T4	Negative	3.0435	3.0	1.2409
T5	Negative	1.8696	1.0	1.2472
T6	Positive	6.1304	6.0652	1.1657

Table C2. Parametric Validation Results.

	SWT t-value	p-value	KST t-value	p-value
# RLV	0.875	0.010	0.955	5.858e-30
# Failed Atmpt	0.744	7.585e-5	0.660	6.404e-10
# Vehicle Col.	0.557	4.742e-7	0.50	1.306e-5
Trial Duration	0.946	0.262	1.0	0.0
# Rej. Gaps (N)	0.959	0.460	1.0	0.0
# Rej. Gaps (Filt.)	0.950	0.311	1.0	0.0
	$\alpha = 0.05$			

Table C3. Paired T-Test statistics for the IGE trial effect.

Inquiry	t-value	p-value
Number of cars	2.8903	**0.0088**
Car sizes	0.5466	0.5904
Car speeds	2.1877	**0.0401**
Proximity to cars	1.8086	0.0849
Pedestrian signal	3.4803	**0.0022**
Others crossing	1.8017	0.0860
Others observing me	1.7390	0.0967
	$\alpha = 0.05$	

Table C4. Significance metrics

	Sex		Driver's license?		Age group		Witness accident?		Involved accident?	
	t-value	p-value	t-value	p-value	t-value	p-value	t-value	p-value	t-value	p-value
Crossing signal violations	89.5	0.041	50.0	0.179	2.424	0.79	6.95	0.031	1.6	0.45
Failed crossing attempts	76.5	0.23	34.0	0.96	3.24	0.66	2.56	0.28	1.6	0.45
Vehicle collisions	65.5	0.58	50.0	0.1	1.56	0.91	6.7	0.035	7.998	0.018
Trial duration	−1.734	0.098	−1.93	0.071	0.782	0.58	1.49	0.25	0.44	0.65
Rejected gaps (naive)	−1.61	0.12	−1.56	0.138	0.6	0.7	1.69	0.22	0.34	0.72
Rejected gaps (filtered))	−0.91	0.37	−0.22	0.83	0.2	0.958	0.399	0.678	0.19	0.828

Appendix D. Participant responses to in-simulation and in-reality influences on their crossing behavior

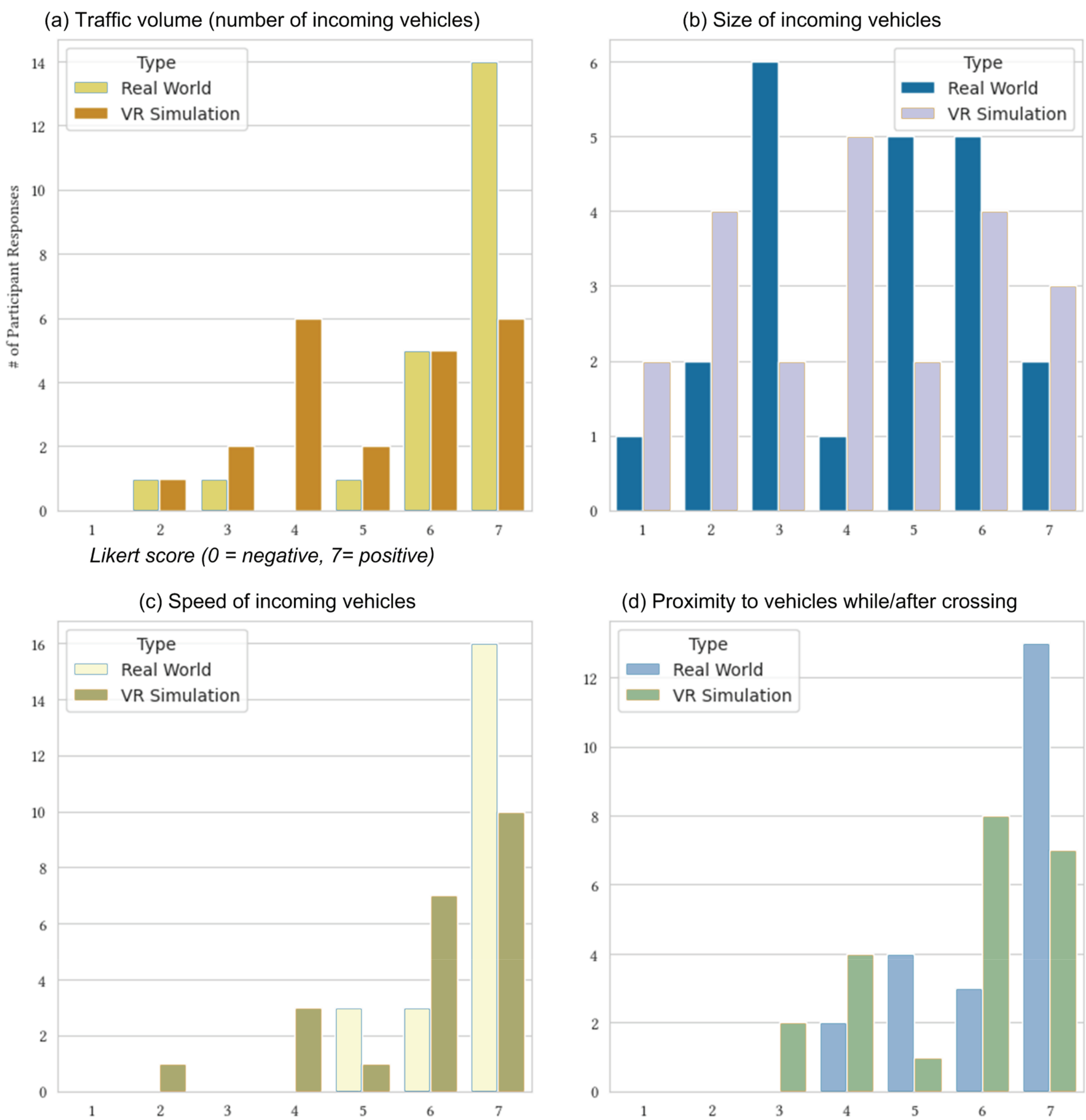

Figure D1. Participant responses to which ***vehicle-based factors*** influence their crossing behaviour in real-world scenarios and the simulation. We show self-reported responses for their real-world behaviour and their behaviour in the simulation trials.

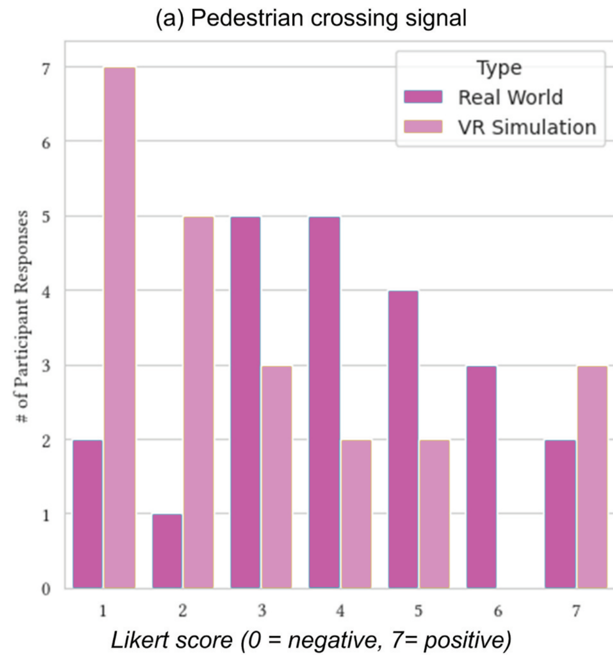

Figure D2. Participant responses to whether the presence of a ***pedestrian crossing signal*** influences their crossing behaviour in real-world scenarios and the simulation. We show self-reported responses for their real-world behaviour and their behaviour in the simulation trials.

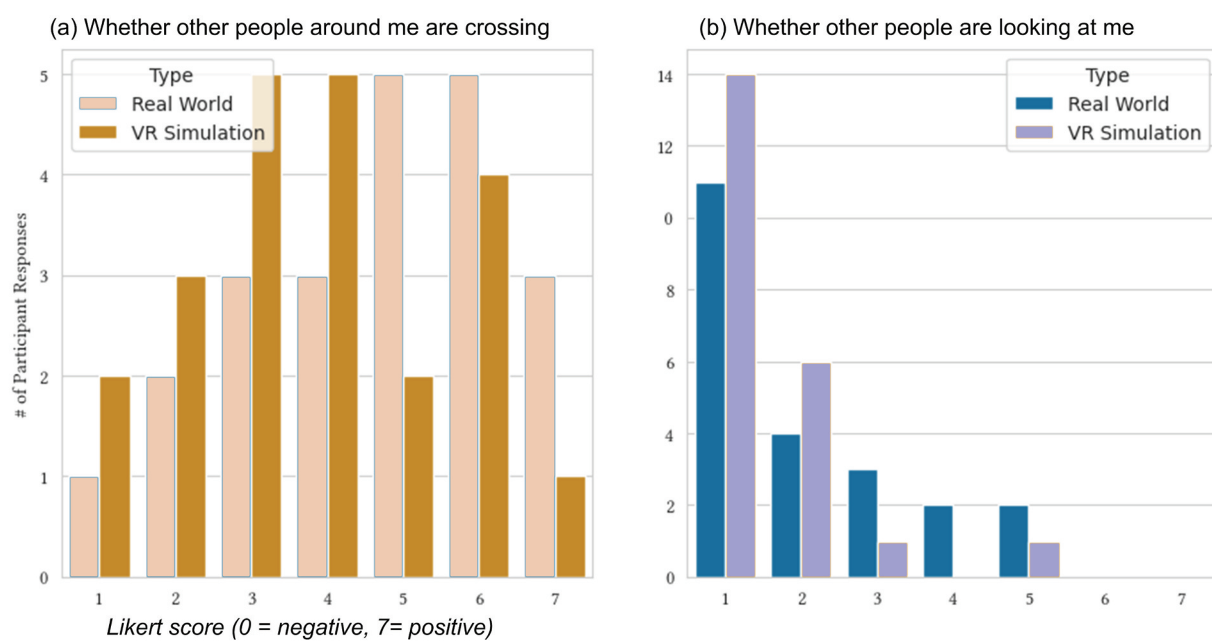

Figure D3. Participant responses to whether ***ambient pedestrians*** influence their crossing behaviour in real-world scenarios and the simulation. We show self-reported responses for their real-world behaviour and their behaviour in the simulation trials.

Appendix E. Detailed Likert responses to presence, plausibility, and performance during the in-simulation trials

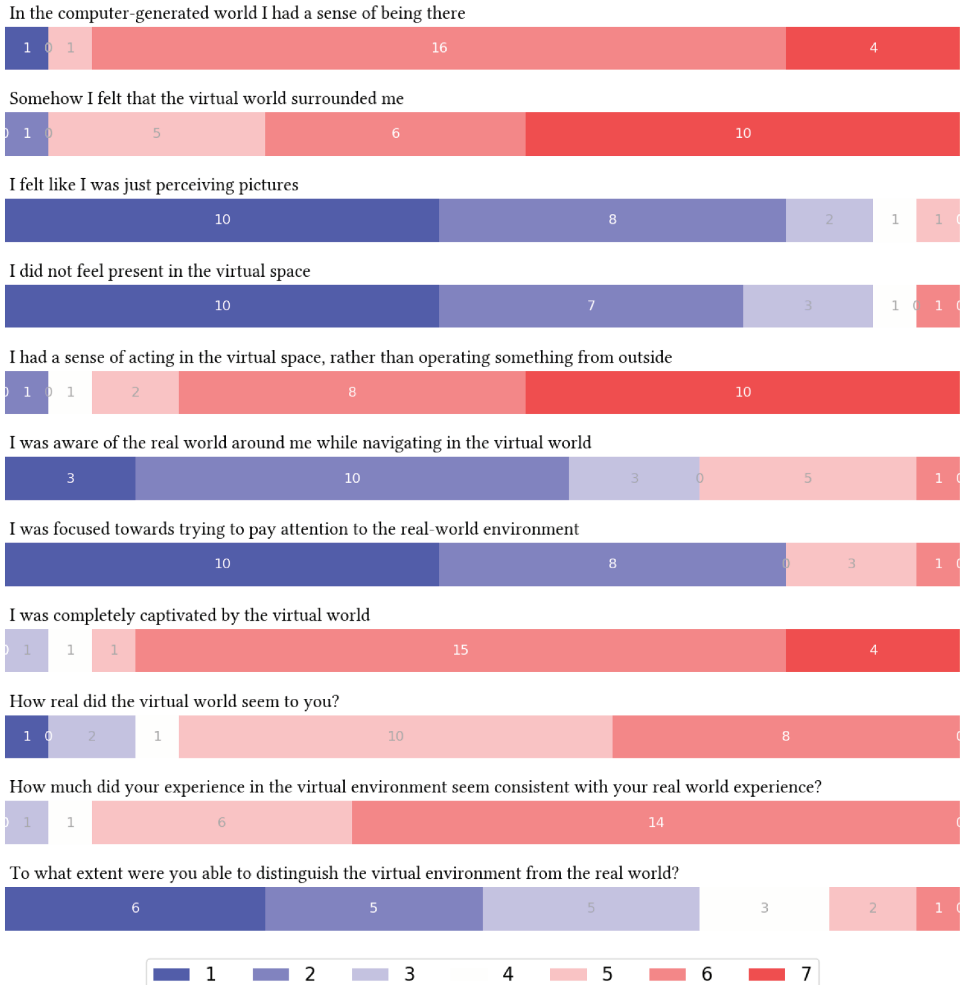

Figure E1. Aggregated responses to ***presence questions***.

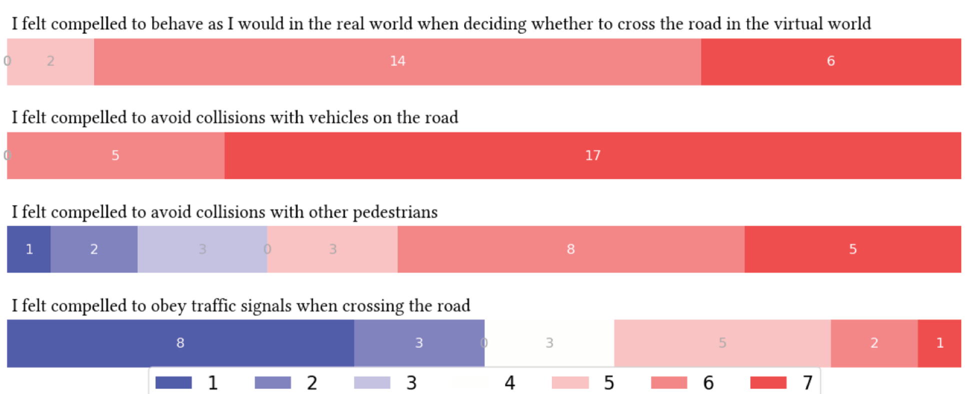

Figure E2. Aggregated responses to ***plausibility questions***.

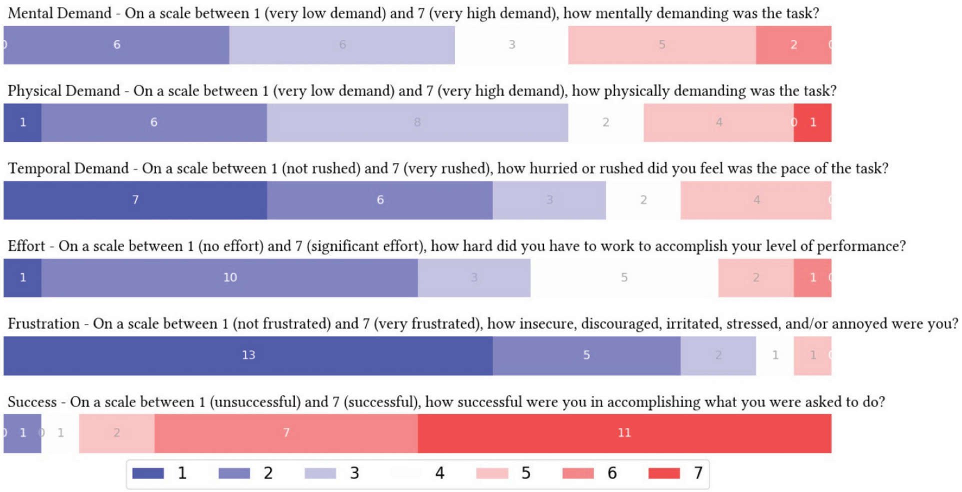

Figure E3. Aggregated responses to ***performance questions***.

Appendix F. Differences during in-simulation behavior by participant demographic

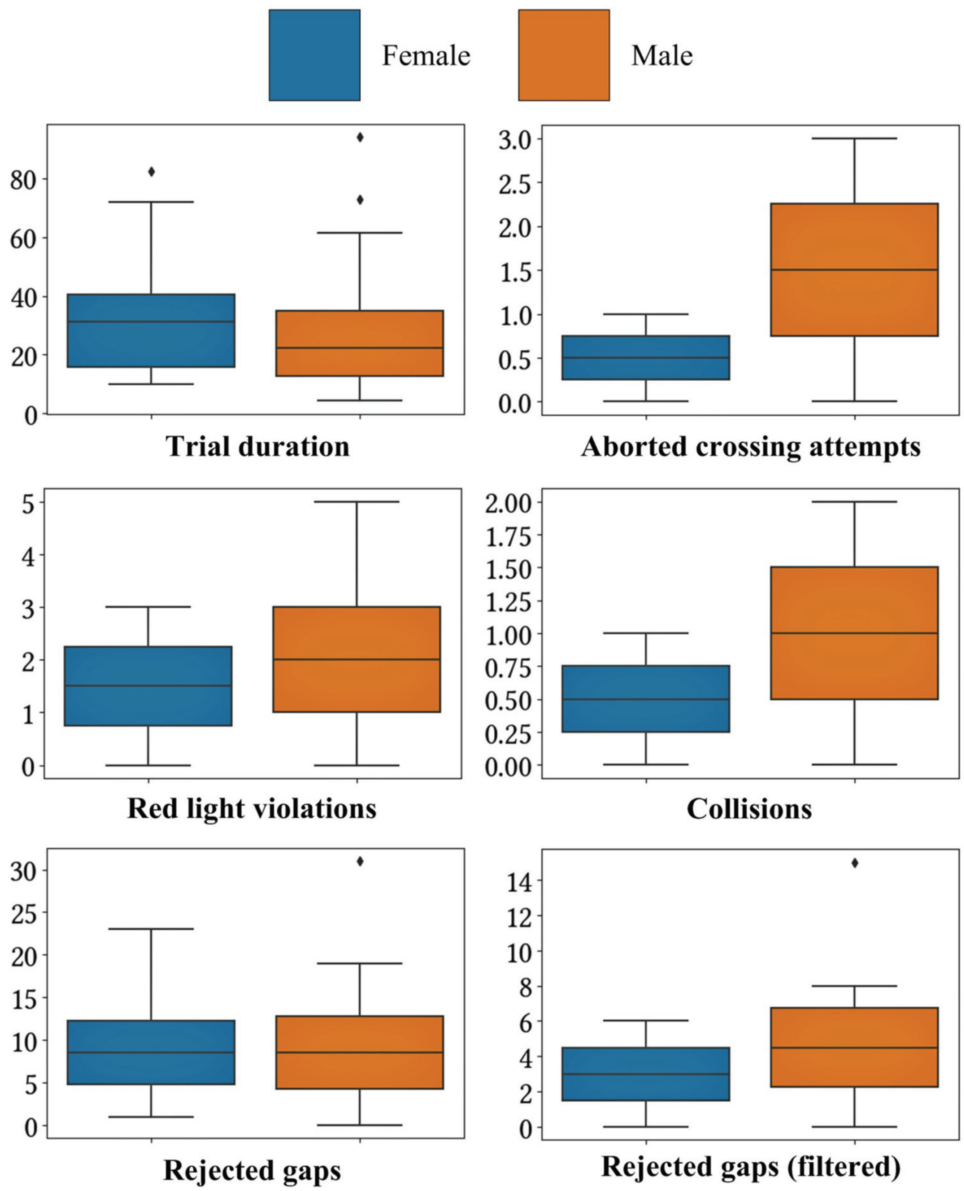

Figure F1. Sex-based variation.

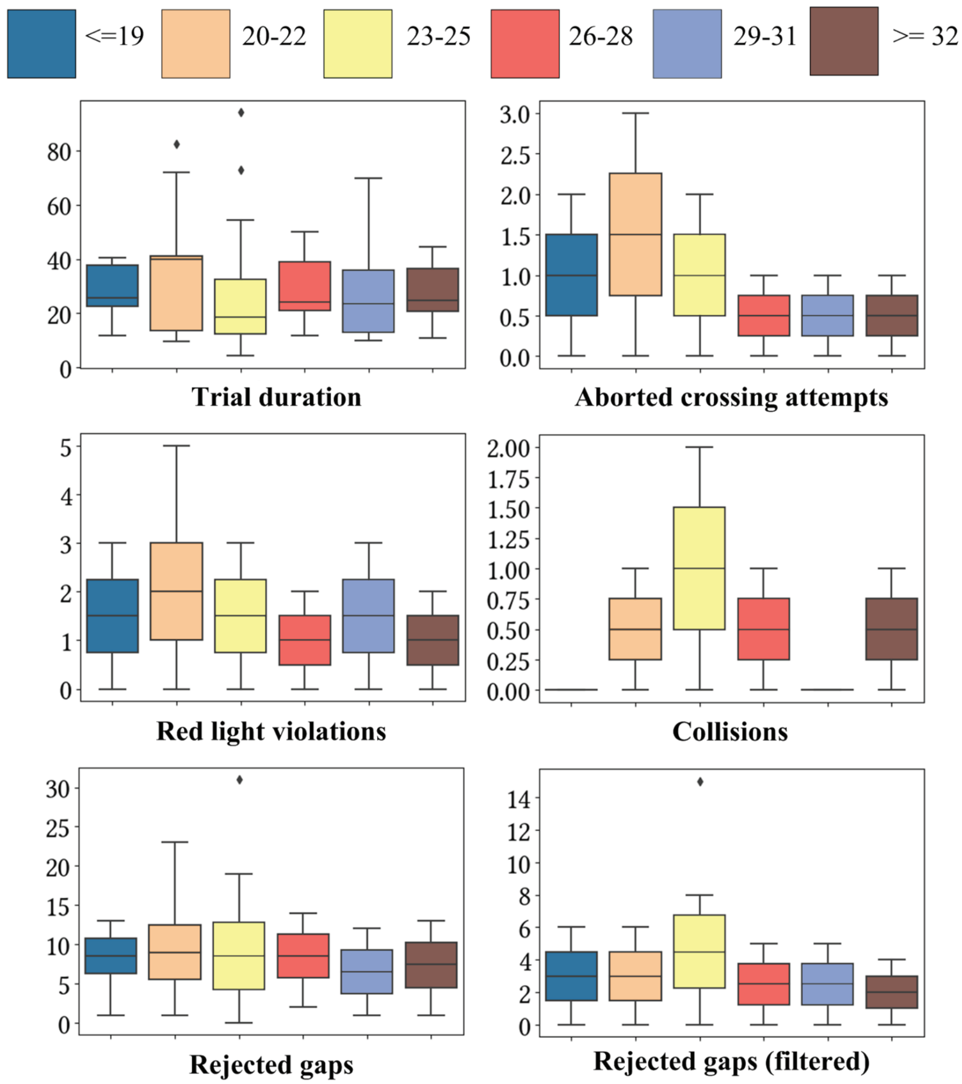

Figure F2. Age group variation.

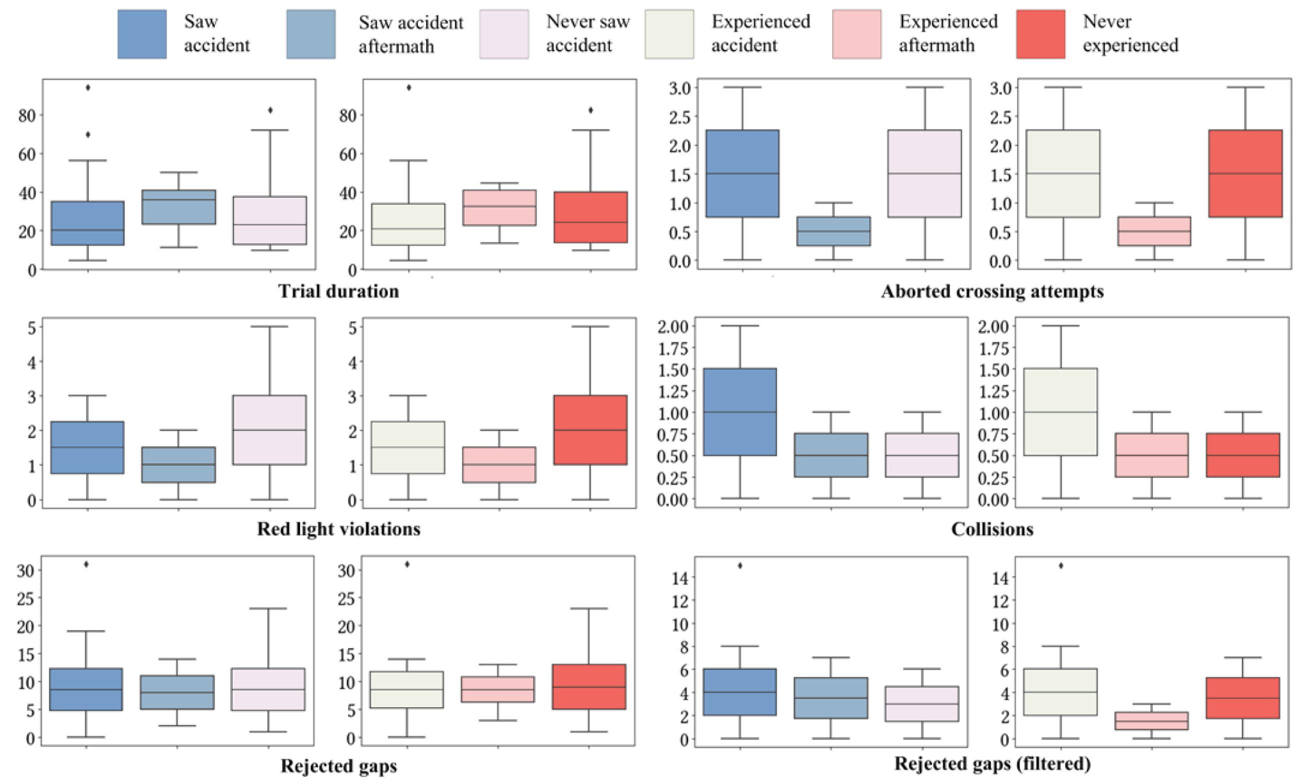

Figure F3. Variation by participant prior experience.