Building Verisimilitude in VR With High-Fidelity Local Action Models: A Demonstration Supporting Road-Crossing Experiments

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Fig. 1. A moment in time and panic in one of our participants who recognized an approaching car too late. Participants were inserted into a Virtual Reality Environment (VRE) to test the effect of a microscopic traffic flow model and behavioral tree algorithm on road-crossing behaviors. VR offers many affordances atypical in standard, real-world observational studies such as the ability to conduct dangerous and risky scenarios in the safety of a lab room.

Virtual Reality (VR) is increasingly useful for experimentation with human-involved scenarios that are hard to access and dangerous to conduct in reality. There is growing incentive for VR to supplement real-world observational studies, and therefore new attention to the performance of VR assets relative to their real-world counterparts. Here, we examine how issues of investigative and experimental parity between real-world domain science and VR involving human-environment behavior might be advanced, particularly in the use case of safety science for road-crossing. Our contribution centers on a VR-based traffic flow simulation to recreate, with high-fidelity relative to the real-world, dynamics of hyper-local interaction between traffic, people, and the roadside environment. This is approached through novelty in provision of local action models for VR assets, based on realistic treatment of small-scale dynamics of traffic flow with matching agent-based pedestrian behavior trees. We show an end-to-end system that facilitates human immersion in what-if VR simulation and an experimental pipeline that supports within-subjects user behavior studies that are capable of revealing user perception of their experience in the experimental domain as well in VR as a graphical medium. An initial demonstration of the system shows that 22 participants ultimately responded with high levels of presence, and with high propensity toward natural behavior across road-crossing dimensions. We report these findings even with low-resolution graphic elements. Our results highlight that high levels of user-identified *contextual verisimilitude* (i.e., appearing authentic, particularly to the senses), alongside *behavioral fidelity* (i.e., exactness, particularly relative to users' knowledge of and experience with real-world counterparts) can be achieved, even with low-resolution graphical depictions. The key, we argue, is the design of appropriate low-level action models to drive user embodiment relative to VR assets. We contend that this finding has wider relevance to consideration of potential channels for VR experience more generally.

CCS Concepts: • **Human-centered computing** → *User studies*; **Virtual reality**; • **Computing methodologies** → **Interactive simulation**; **Simulation evaluation**.

Additional Key Words and Phrases: Virtual reality, Pedestrian, Simulation, Microscopic traffic flow, AI, Behavioral tree, Pathfinding, 3D interaction, Presence, Realism, Task load, Embodiment

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1 INTRODUCTION

Virtual reality (VR) is widely considered a viable investigative tool for studying human responses to real-world phenomena via simulation, particularly for circumstances that may otherwise prove hazardous or out-of-reach to testing in physical realities. The case of evaluating human road-crossing dynamics, for example, has proven how VR can eliminate risk to human subjects in experimentation and can afford entirely new means of evaluating people's perception, action, and cognition relative to crossing design and traffic patterns [Camara et al. 2020a,b; McComas et al. 2002; Mohler et al. 2004; Sobhani et al. 2017]. VR has been shown to facilitate simulation-based experiments with real human users that allow the study of crossing behavior across demographic groups [Deb et al. 2020; Morrongiello et al. 2015; Schwebel et al. 2008a; Wang et al. 2022], crowd dynamics [Koilias et al. 2020; Nelson et al. 2020; Rio et al. 2018], and traffic behaviors [Bhagavathula et al. 2018; Deb et al. 2017; Simpson et al. 2003a]. These factors of crossing phenomena are largely opaque to any sort of academic inquiry or engineering intervention by other means, save by observation that is prone to immutable barriers of observational bias (whether performed by human observers or by machine learning) and subject obscuration in scenes with even a few people or vehicles. VR simulations of crossing scenarios essentially ease these concerns, at least in principle. Yet, in doing so VR introduces additional sets of problems that must be navigated. In particular, challenges abound in bringing VR to situational and behavioral parity with real-world counterpart phenomena and scenes, and in faithfully representing life-like experiences for VR users in ways that can evoke real matching behavioral responses in model experiments.

Existing VR models of road-crossing have shown significant promise in easing some of these concerns. Indeed, many benefits afforded by VR over traditional in-the-wild observational studies include controllability, reproducibility, standardization, ease in data collection, safety, and novel feedback and instruction paradigms [Colley et al. 2019; de Winter and Happee 2012]. VR has been used to support road-crossing research across a variety of promising experimental axes, including investigating accident avoidance opportunities [Simpson et al. 2003b], the impact of ADHD on crossers [Clancy et al. 2006], design factors of crosswalks [Kwon et al. 2022], specifics of children's road-crossing [Schwebel et al. 2008b], and the geography of crossers' attention [Torrens and Gu 2023] and social gaze [Torrens and Gu 2021]. The question of whether VR can reliably induce behavior is omnipresent, and it is particularly relevant in social and behavioral science. The question has been examined in particular for behavioral geography [Bailenson et al. 2003], which has relevance to our application domain of road-crossing. Additionally, anecdotal evidence and questionnaires for road-crossing specifically have shown that VR scored high in user presence and immersion [Feldstein et al. 2016; Simpson et al. 2003a] and that metrics such as real-world walking speed, gap acceptance, and vehicle distance estimation were similarly replicated in virtual reality environments (VREs) [Angulo et al. 2022; Bhagavathula et al. 2018; Deb et al. 2017]. This would seem to indicate that the safety science community believes that VR has application viability in road crossing studies. Indeed, it is possible that there are a variety of adjacent application areas in which VR simulations of road-crossing could have great currency, including examination of the performance of autonomous vehicles (AVs) in pedestrian scenarios [Deb et al. 2020, 2018], exploring navigation methods in virtual cities [Savino et al. 2019], and investigating clinical conditions that affect spatial or temporal processing [Clancy et al. 2006; Kim et al. 2010; Wagner et al. 2021].

In this paper, we aim to advance the current state-of-the-art in VR experimentation of road-crossing in two important ways. First, we aim to build VR platforms that have high *fidelity* relative to real-world counterparts, i.e., their underlying processes that drive animation are faithful to real-world or theoretically-supposed mechanisms. We contend that many existing VR models rely on relatively simple heuristics for pedestrian and vehicle behavior, which end up artificially and perhaps unnecessarily constraining the application value of VR. Second, we aim to produce VR experiences with high *verisimilitude*, i.e., they appear and seem to the user with convincing authenticity in ways that will elicit real behaviors from participants. Treating fidelity and verisimilitude, we offer, can greatly expand and deepen the ontological value of VR experiments, leading to richer opportunities for knowledge discovery in VR.

In brief, our approach involves exploring the effects of varying human contexts on the induction of real-world road crossing strategies in VR-based pedestrian simulators, as well as identifying key design patterns that enhance or reduce that effect. To accomplish this, we introduced a within-subjects user study with a custom-built VR pedestrian simulator that utilized stochastic, micro-scale, and local-action traffic models and behavior trees to facilitate vehicle and pedestrian movements respectively. The simulator involves three major systems: virtual vehicles driven by a microscopic traffic flow model, a virtual traffic system that models a finite state machine to switch between different signal lights, and virtual pedestrians whose movement follows a behavioral tree that interacts with vehicles and traffic signals to determine when to cross the road. On top of this substrate, we developed a user-monitoring pipeline to assess real human participants' uptake of the simulation scenario relative to (1) components of VR as a modality that is able to invoke real-world behavior from users, and (2) components of the phenomenological simulation to assess whether empirical results produced through experiences in VR could be diagnostically valid relative to theoretical ideas in safety science and observational outcomes in the literature on road-crossing. Our evaluation on both counts is based on objective metrics and qualitatively empirical anecdotes polled from user experience in a range of VR experiments with our system.

The key innovation of our paper is the implementation of mathematically tractable local action models (specifically microscopic traffic flow models and behavioral trees designed to operate at scales of space and time that match to road-crossing pedestrians' small windows of decision-making relative to roadside events) and their operational application in VR with verisimilitude to convince users with sufficient levels of immersion and presence to evoke realistic embodied behavior (particularly embodiment that would establish a plausible and nuanced sense of risk and hesitation), and high-fidelity relative to real roadside entities and events that would also allow us to assess simulation results in ways that could "map back" to open problems in the theoretical literature. Our results show that our approach can be successful in these regards. We demonstrate, in particular, that participants who interacted with our VR system were persuaded by the verisimilitude to induce risk avoidance strategies employed in real-world road crossing scenarios, and that they did so out of high feelings of immersion and presence in the VR environment, and a high degree of appreciation in the authenticity of the behavior of the VR assets. We additionally found that verisimilitude and fidelity held in the VR, even when we used low-resolution graphical/visual assets in the simulation.

Our findings matter to the computer graphics community and to the domain sciences that rely on those graphics for a few important reasons. In tackling the fidelity and verisimilitude dimensions of VR experiments together, we argue that VR can be better positioned to produce model environments that are more realistic and believable. These qualities are shared across many other possible applications of VR, as well as in broader applications of simulation-based computer graphics and animation more generally. Looking at VR's popularity and rising prominence in emerging topics of safety science, particularly the potential for autonomous vehicle simulations to train deep learning schemes for sensorimotor control relative to crossing pedestrians [Camara et al. 2020a,b; Dosovitskiy et al. 2017], it is likely that the future will see VR replace real-world observational studies in many respects due to the safety, controllability, and amount of high-resolution data that VR can produce. To prepare for that potential outcome, further analysis into the introduction of vehicle and pedestrian behaviors that more closely resemble the unobservable and humanistic decision-making processes inherent in real-world interactions is required. However, this task is easier said than done, for the design and implementation of the virtual environments and all dynamic elements therein such as vehicles, pedestrians, and traffic signal behavior must be carefully adjusted to account for detailed individual, dyadic, physical, social, and human-environment behaviors while also controlling for VR-specific factors such as immersion, presence, and simulator sickness (SS). The fact that perceptual differences of virtual environments can occur between observers [Slater 2009] highlights how crucial it is for VR-based pedestrian simulations to provide users with enough visual and interactive opportunities to induce them into behaving as they would in the real world. In that spirit, this paper addresses both increased sensitivity to human behavior while using VR as a graphical medium for experimentation, as well as tackling the replication of authentic graphics conveying human behavior as simulated content.

2 RELATED WORKS

2.1 Modeling Virtual Traffic Flow and Movement

Due in part to long-standing success in the computer graphics community's development of car dynamics for film (e.g., *Pixar™*'s "Cars™" series) and for video games (e.g., *Playground Games™*' "Forza™" titles), many VR-based models of road-crossing have proceeded from a vehicle-first approach, i.e., the bulk of the simulation effort is invested in producing plausible vehicle control and/or traffic dynamics. This practice also follows the availability of well-developed heuristics for macro-traffic dynamics (especially traffic congestion phenomena) in physics [Nagatani 2002], particularly using cellular and agent automata models [Kai Nagel and Michael Schreckenberg 1992; Rickert et al. 1996; Schreckenberg et al. 2001; Torrens 2004; Wagner et al. 1997; Zhang 1999] that can conveniently and efficiently match to vehicle-characters in animation scenes with low computational overhead. Macro-traffic models have a significant limitation for the sorts of human-behavioral road-crossing type experiments that we discuss in this paper: individual people react to (and in tandem with) vehicles [Ishaque and Noland 2008]. Critically, at the roadside people do so over very small and fleeting windows of space and time (through so-called gap acceptance [Harrell 1991a; Kadali and Vedagiri 2013; Liu and Tung 2014a; Onelcin and Alver 2015]). Real pedestrians do not generally perceive macro-conditions of traffic behavior, nor do pedestrians marshal their behavior at scales of space and time that align with macro-traffic phenomena (i.e., dynamics of traffic over large queues of cars). For example, pedestrians see that a car is stopped, not that it is a component of a neighborhood- or road-level process of traffic congestion. In short, the behavior of vehicles produced in traffic models in VR simulations is *out of phase* with the behavior of human pedestrians; as such, attempting to connect the two is generally going to be a losing proposition for VR that is intended for applied experimentation (although perhaps it is acceptable for graphics designed purely to entertain). Indeed, pedestrians, and the dynamics that they conjure relative to vehicles and to crossing environments and infrastructure, have received comparatively less attention in VR simulations of roadside phenomena, even though crossing is a generic process within almost any urban scene. A fundamental contribution of this paper is to show that *both* pedestrians and vehicles can be drawn into parity of experimental exchange within VR, and that this can be done in the situational context of roadside scenes and infrastructure. Our contention is that this can be achieved by aligning (1) the fidelity of pedestrian simulation and vehicle simulation in the underlying mathematical models that drive them, and (2) tying that alignment to VR users' expectations for verisimilitude.

This idea builds upon what we consider a chief limitation of traffic models as they are commonly developed in VR simulations (and in many domain science simulations more generally): that they are not designed for plausibility at micro-scales, particularly at the scales of interaction that human users of VR would need to establish (1) plausibility of traffic scenes in simulation, and (2) to evoke realistic behavior from those users. What we will term here to be a "plausibility gap" stems, we contend, from the common-held practice of using proxy mathematics of traffic dynamics and physics of flow in lieu of *driver behavior*. This is of course an acceptable accommodation in traffic studies, where system-level properties, say of traffic over an urban area, are the object of simulation [McFadden 2007]. In VR, however, these proxy models can often create significant disjoint relative to real-world experience when users, who are often examining the vehicle behavior that the models produce from an up-close perspective, encounter them and consider how to respond. It is perhaps quite easy for the plausibility of vehicle models to falter upon inspection by a VR user because the underlying models lack serious treatment of driver behavior generally, and because they specifically do not account for the highly dynamic control that real human users have over their VR avatars. If these disjoints occur, the illusion of VR as a simulacrum is diminished, and with it there may be a commensurate decline in its efficacy for experimentation.

Existing studies that rely on pedestrian simulations typically utilize vehicle movement models that are hard-coded to control for partial and often quite specific pedestrian-vehicle interactions. For example, a usual approach sees the applications of predetermined constant vehicle speeds [Bhagavathula et al. 2018; Deb et al. 2020; Feldstein et al. 2016; Morrongiello et al. 2015; Simpson et al. 2003a; Torrens and Gu 2021; Wagner et al. 2021; Wang et al. 2022] and gap distances [Clancy et al. 2006; Deb et al. 2020; Feldstein et al. 2016; Morrongiello et al. 2015; Schwebel et al. 2008a; Simpson et al. 2003a; Wagner et al. 2021; Wang et al. 2022], paired with pedestrian models to produce distinct experimental conditions. It is important to highlight that factors such as gap acceptance, crossing effort, pedestrian timing between acknowledgement of hazards and reaction, and pedestrians' sense of their own skills and affordances in crossing opportunities are all *behavioral* factors sourced in perception and cognition [Cambon de Lavalette et al. 2009] over small and subtle fleeting windows of opportunity and interaction in crossing. Most existing mathematical models reduce all of this to a simple and straightforward parameter value (usually a constant). Moreover, when applied to explain behavior of pedestrian archetypes, the usual treatment of those archetypes is to assume unanimity in description: modeled pedestrians are very often treated in models as if they all act in the same way, like there is some "universal pedestrian" (although research tells us that pedestrian behavior varies markedly, for example, by age [Oxley et al. 2005a], by risk threshold [Sueur et al. 2013], by their timing acumen [te Velde et al. 2005], based on their motivation [Yagil 2000] etc.). Usually, traffic models further rely on assumptions that pedestrian actions are hyper-rational (e.g., maximizing some system function of traffic dynamics in ways that no human being would every really do). This, we contend, is a vestige of the formulation of the underlying *action models* that are tasked with producing traffic (and then which become the only option for docking pedestrian behavior, essentially "pulling" the model description of the pedestrian to the simplicity of the car model so that they exchange parameter values). For example, existing inter-vehicle relational movement models are generally represented with mathematics designed to borrow driving patterns from physics of granular and mobile media [Baxter and Behringer 1990]: essentially, they are particle traffic models, which describe the details and interactions of traffic flow [Popping 2013] from a bottom–up perspective. Particle traffic models tend to treat vehicles as force-attracted and repulsed collectives or continua of agents, dynamics for which are conveniently represented using point-sources (in granular and gaseous flow [Baxter and Behringer 1990], or even flocking routines [Reynolds 1987a]) with simple velocity that can come from a broad range of parsimonious mathematics that can facilitate–but only really at system levels of large-scale patterns of traffic, say on a highway–complex-systems behavior in response to tunable parameters for other vehicles and road conditions [Helbing 2001; Son et al. 2022]. Invariably, this is done sensibly, so that the micro-models can generate "macroscopic" outcomes that have an explanatory correlation with broader concerns such as continuum mechanics or the evolution of phase shifts in traffic evolution, both accessible through partial differential equations for rapid, coarse estimation of vehicle movements within a phenomenological (top-down) perspective [Son et al. 2022].

Microscopic and macroscopic models both have been shown to predict and simulate traffic dynamics in the real world [Chu et al. 2011] (again, we make the observation that these are not pedestrian-vehicle interactive dynamics, but rather dynamics of car-to-car action and response). However, as VR brings users physically closer to virtual vehicles, there is a greater chance for users to closely scrutinize the movement behavior of the vehicles that they encounter as graphical objects and characters [Torrens and Gu 2021]. Building plausible vehicle scenarios that will allow enough granularity and fidelity to support applied experiments into human behavior at the road-side is hard, again we point out, because the two processes that need to interleave—human user behavior and vehicle driving heuristics—are fundamentally out of phase with each other. To address this disparity, vehicle movements must demonstrate enough complexity to be realistic-appearing at close quarters, and they ought to provide mechanisms for the embodiment of human-like behaviors that can convince or entice users into treating vehicles as objects for their attention and interaction, specifically as potential collision threats that will cause vigilance, hesitation, caution, rule-following, and other safe behaviors at the roadside. Here, we argue that this can be achieved through local action models that appear to *authentically* produce agent-based behavior in vehicles through interactions with other vehicles and the environment.

Fortunately, we are not starting from a clean slate in thinking of ways to address local action modeling of vehicles. Two classes of microscopic vehicle control models are available from the existing research and development landscape. Queue-based car-following models [Lenz et al. 1999], also known as time-continuous models, are characterized by ordinary differentiable equations that describe each vehicle's position and velocity. Vehicle agents in these models rely heavily on a leading vehicle to determine their own acceleration, represented as an equation that takes values such as the velocity and bumper-to-bumper distance known as "headway" between the current vehicle and its leading vehicle. Examples of car-following models include Gipps' model [Gipps 1981], and the Intelligent Driver Model [Treiber et al. 2000]. In contrast, cellular automata models define vehicle dynamics based on the discretization of available movement space and time. Vehicles, usually represented as car-sized sections of road within this discretization, determine their acceleration based on how finely discretized the road is, their current velocity, and change in time. Examples of cellular automata models include the Biham-Middleton-Levine Traffic Model [Biham et al. 1992] and the Nagel-Schreckenberg Model [Kai Nagel and Michael Schreckenberg 1992]. Unfortunately, no single model has been adequately demonstrated to fully predict movement metrics derived from real-world vehicles [Knorr and Schreckenberg 2012; Punzo and Simonelli 2005]. As such, the choice of which microscopic vehicle control model to use in pedestrian simulators must be highly dependent on the needs and context of the simulation. For example, if vehicles in the simulation are limited to single lanes without lane transfers and vehicles are expected to slow down or speed up with respect to obstacles or traffic signals, then a microscopic vehicle control model that provides smooth deceleration and acceleration between follower and leader cars would be ideal. As we will detail shortly, the Intelligent Driver Model provides a good starting point for our use scenarios in this paper.

2.2 Modeling Virtual Pedestrian and Crowd Dynamics

A wide array of model approaches for treating the movement of virtual pedestrians have been developed, with significant levels of specialization within different application domains including urban design and planning [Turner and Penn 2002], transportation studies [Moulin et al. 2004], physics for understanding complex adaptive systems [Helbing and Molnár 1995], investigations into pedestrian flocking and herding behavior of structured groups [Gu and Deng 2011], dynamics of escape and panic behavior in emergency scenarios [Helbing et al. 2000a], and studies of kinesiology and biology of walking [Badler et al. 1994, 1987; Girard 1991; Zhao and Badler 1994]. For all of their sophistication relative to their applied domains, a unified model of pedestrian movement *also* remains elusive, largely because of the high level of uniqueness in walking behavior that comes as a by-product of the variation in human physiology and differences in human behavior as sourced from perception and cognition [Wang and Cutting 1999].

Various advances toward a unified model have, however, been approached in the computer graphics literature [Pelechano et al. 2008], where the design goal of generating realistic-*looking* pedestrian movement (rather than authentic behavior) is often the concern. These include early graphics and animation work by Reynolds [Reynolds 2006, 1982, 1987b, 1993; Reynolds et al. 1999] in deriving parsimonious rules and plausible *patterns* for flocking and steering behavior. Continuum models have also been developed across a variety of considerations that facilitate easy deployment in animation, including work on vector fields [Treuille et al. 2006] and navigation graphs [Sud et al. 2008a,b] that allow real-time simulation of crowds of walkers at very large volumes of interacting entities [Gayle et al. 2009; Patil et al. 2011; Salomon et al. 2003]. A promising thread of research opened up around building animated virtual humans from caches of motion capture data as well as video data [Favaretto et al. 2016; Hoogendoorn et al. 2003; Lee et al. 2007; Makris and Ellis 2002], largely through and fast-resolvable procedural and heuristic rules [Badler et al. 1994; Faloutsos et al. 2001; Girard 1991; Gleicher 1998; Gleicher et al. 2008; Kovar and Gleicher 2003a; Kovar et al. 2008]. These approaches are fantastically useful for building procedural crowds and other VR assets. For the applications in our paper, we need an alternative approach, as we require VR assets that can can interact with users in ways that (1) evoke a true behavioral response or signal, and (2) that have fidelity in reasonably exactly matching the behavioral dynamics of their real-world counterparts.

Much of the existing work to develop authentic patterns of movement or realistic individual movement functionality for pedestrians and synthetic human characters in animation can also be regarded as "agent-based", which perhaps raises a small poimnt of confusion in terminology between our approach and the existing range of literature in computer graphics and animation. What we might usefully term as "procedurally agent-based" models (akin to Reynolds-type boids or gaming non-player characters running around on mesh-based roadmaps) define a set of transition functions that can poll from stationary conditions of a synthetic walker, and then animate those rules as the walkers encounter information upon proceeding through an environment composed of graphical objects and state-based objects (geometries to avoid and see, as well as information bound by other agents as finite state machines). Much of these collision routines are resolvable using well-known heuristics from motion planning [Lenz et al. 1999] and graph search [Latombe 1991], especially when considered in metric spaces such as urban infrastructure. We will also use this type of agent *mechanism* in our model–at a fundamental level, we rely on finite state machines–but we emphasize here that our transition functions are not procedurally-based. We acknowledge that Reynolds-type models have addressed movement of characters in ways that provide insight to domain science (particularly behavioral geography), e.g., by offering heuristic exploration of the relatively long-run problem of resolving paths through graphics meshes and fields of collision objects in ways that shed light on real world issues of trip-making and way-finding [Torrens 2016]. In some case, procedurally agent-based models have been refined in ways that relate that movement back to domain science such as behavioral aspects of perception such as vision, for example through the work of Terzopoulos [Rabie and Terzopoulos 2000; Terzopoulos 1983, 2003; Terzopoulos and Qureshi 2011; Terzopoulos et al. 1994; Yu and Terzopoulos 2007], and to social decision-making through the work of Badler and colleagues [Allbeck and Badler 2008; Badler et al. 1997; Durupınar et al. 2011; Durupinar et al. 2011; Pelechano and Badler 2006; Pelechano Gómez et al. 2005], as well as success in representing inter-personal influences in appearance judgments that have been notably uncovered in graphics through the work of O'Sullivan and colleagues [Dobbyn et al. 2005; Kavan et al. 2008; McDonnell et al. 2008a,b]. The establishment of ways to relate human movement to **presence** in graphics has been key to the latter-mentioned stream of work [Allbeck and Badler 2002; Stocker et al. 2008]. This is a thread that we will pick up in our aim here to (1) weave connections between VR simulations and real-world counterpart phenomena at road crossings, and to establish (2) presence-based experiences for users through faithful reproduction in VR.

2.3 Limitations in Current Virtual Simulations

Our aim is to improve VR fidelity and verisimilitude: this necessitates that we provide for assessment of the usefulness of our approach. Despite VR's attractive qualities as a laboratory for experiments with things that are difficult or costly to tinker with in reality, there still remain distinct obstacles that prevent full adoption of VR-based simulations in lieu of real-world observational studies. The existing literature on VR-based simulation involving pedestrians, for example, points to some critical obstacles and design choices that are crucial to consider when creating a virtual simulation that replicates real-world conditions. Coupled with this challenge, VR still continues to struggle in many dimensions of representing real-seeming immersive experiences that map convincingly to users' natural abilities and senses [Zhang et al. 2022]. Here, we mention a few of these points which are relevant to the system that we will ultimately propose and demonstrate in this paper:

- **Differences in visual/auditory aesthetics** [Feldstein et al. 2016; Koilias et al. 2020; Simeone et al. 2017] **and vehicle/pedestrian behavior** [Angulo et al. 2022] between the virtual environment and real world may alter users' movement behavior in VR as a result of diverging expectations of how the simulation ought to behave.
- **Lack of ego-self-representation** may make it difficult for people to be fully immersed or judge their body position in regard to interpersonal interactions with pedestrians [Koilias et al. 2020; Mousas et al. 2019].
- **Preconceived attitudes towards the nature of VR** may prematurely establish disjoints in perceptions and behavior towards virtual agents controlled by computers as opposed to virtual avatars controlled by people [Bailenson et al. 2003]. It is possible that these preconceived notions might induce players to feel like the virtual simulation is like a game, thereby reducing the likelihood of real-world strategies being replicated [Wang et al. 2022].
- **Limitations in hardware** such as the use of a tethered headset [Simpson et al. 2003a; Torrens and Gu 2021] or a limited visible FOV [Clancy et al. 2006; Simpson et al. 2003a] may also prevent users from being fully immersed in simulations. Fortunately, many of these limitations will become less relevant with future hardware.
- **Space constraints may limit the amount of room that users physically have to move around in.** Space will likely almost always be in shorter supply in experimental studio and lab-type facilities than it could be in the open territory of the real world. This could possibly be addressed through simulation tricks such as redirected walking [Razzaque et al. 2002], although algorithmic redirection would seemingly break the ability of VR to remain faithful to natural experiences of walking and steering if it is used beyond a few meters of traversal. Redirected walking is unlikely to be the solution in experiments that seek to elicit real human movement responses. Other approaches based on large-factor treadmills (e.g., the *Sarcos Treadport* [Mohler et al. 2004]) with adjustable slope may be more suitable, but they remain expensive and add further hazards to participants tripping or stumbling against a mechanical surface; they also usually require users to be harnessed to a series of suspension apparatus which is a non-starter for experiential parity.
- Finally, even if immersion is fully achieved through careful consideration of the visual design and implementation of virtual environments, **personal factors such as fear of collision with real-world objects, fear of damaging expensive equipment, and proclivities to Simulator Sickness through visual-vestibular sensory mismatch [Reason 1978]** may impede users from fully committing to established strategies learned in the real world [Koilias et al. 2020].

Therefore, in addition to transposing realistic-behaving component characters, vehicles, environments, and phenomenon scenarios into VR experiments, it is likely necessary to simultaneously control for a rather large set of general inconsistencies between real and virtual perception and ideation. In particular, careful deliberation about the movement and interaction mechanisms, hardware limitations, often highly-personal proclivities, and unique physiological makeup of individual participants must be taken into account to reduce the chance of these factors influencing data captured during and after experimentation in VREs.

3 MOTIVATIONS BEHIND THE SIMULATION

A first requirement to achieve our aim of finessing fidelity and verisimilitude is to empirically assess human performance in VR against both (1) the simulation as a representation of crossing factors, and (2) the sense and experience of plausibility that VR–as a medium–can furnish to the user relative to their own (often unique and idiosyncratic) expectations for presence. Doing both is, we think, part and parcel of building useful action–response dynamics in VR, and crucial to endowing VR with experimental value. This is useful for the application of VR to what-if-type experimentation, but also more generally in building computer-human interaction capabilities for VR as a mode of conveying graphics and animation-based experiences.

A second (allied) requirement that must be addressed in approaching our aims is for our simulation to tackle the problem of representing realistic-appearing and realistic-acting **behavior** of synthetic agents, specifically virtual vehicles and humans, in VR. Our primary goal outcome in this regard is that a user of that simulation should be able to establish interactive and behavioral **parity** with such synthetic agents. For virtual humans, this idea has been approached thus far mostly for physicality in agency. Examples include character generation by IK/FK-based motion blending [Kovar and Gleicher 2003b], patching [Hyun et al. 2013; Lee et al. 2006; Shum et al. 2008; Yersin et al. 2009], and warping [Witkin and Popović 1995], as well as knowledge discovery and data-mining on motion capture ("mocap") libraries. For virtual vehicles, we would argue, the notion of realism is under-developed outside newer simulation environments for autonomous driving [Dosovitskiy et al. 2017] and virtual driving simulators [Godley et al. 2002], although the sophistication of some video game driving middleware comes very close to mimicking real driving [Wymann et al. 2000].

Here, we contend that there are untapped opportunities available to research community, particularly in the sense that these graphics-based and mathematical approaches can be supplemented and extended with one-to-one mappings based around low-level action models (i.e., models that can supply the behavioral factors and procedures that underpin and generate higher-level dynamics such as macroscopic traffic, which can be handled, transferred to generate macro-scale effects, animated through exhaustive trials, etc. with existing approaches in the existing state-of-the-art). In particular, we contend that these adjustments to the status quo in VR modeling of road crossing, in particular, could produce new ways for users to enact meaningful **behavioral exchanges** with VR assets. This, we think, has value above and beyond the specialized case of crossing models. Our belief, which sits at the heart of this paper, is that doing this in ways that (1) are useful for human-VR interfaces, that (2) allow for realism-based experimentation in VR, and that

(3) can be validated back to meaningful VR experiences for users requires a paired solution to issues of (presence-dependent) participant embodiment in the VR medium and participant embodiment in the simulation as a faithful reproduction of its counterpart realities.

In particular, we will show that embodiment can be regarded as one of the central design channels for building authentic VR experiments: the embodiment of the user with VR as a general medium through issues of egocentric affordance (user-to-object) with graphics, the embodiment of the user with graphical assets in the animation through allocentric affordance (object-to-object), and social-situational embodiment through affective valence between the user, characters as plausibly animated entities, and faithful representations of simulated content.

Again, we are not the first to attempt this, and we acknowledge that these ideas build upon and advance existing threads in both the computer graphics literature and the virtual humans community regarding presence. Our key differentiating approach relative to that existing work is our focus on presence in *simulation content*, which we believe when allied to presence in graphics and VR can help to forge larger and more compelling VR experiences that address both channels of user experience. Ultimately, we are encouraged that this could support more diagnostically useful VR applications in experimental settings.

4 HARDWARE SETUP

The simulation took place in a research lab/studio in an American university. The test space was approximately 11m x 7.52m in total size with a traversable area limited to 8.2m x 3.67m due to furniture and room architecture.

The virtual simulation was developed and run in *Unity3D* ver. 2021.3.11f1 on a PC with an RTX 3070 GPU, 6-core *AMD Ryzen* 5 5000 Processor, and 6 gigabytes of RAM. VR functionality was added to the simulation through *Unity*'s *OpenXR* and *XR Interactions Toolkit* packages, which provide a suite of scripts, components, and back-end infrastructure that afford VR applications to be run on a wide array of VR HMDs. While *OpenXR* also allows for controller-based interactions, no controllers were used in the simulation.

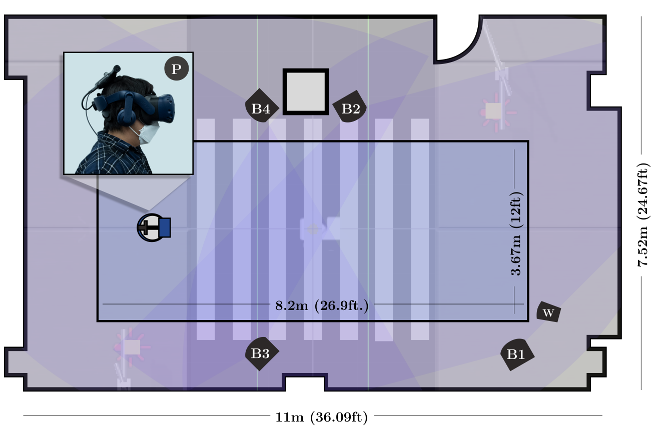

Fig. 2. Architectural layout and Base Station orientations of the SimSpace MoCap Laboratory. Base stations B1-B4 are positioned to ensure that at least one Base Station is within line of sight of the participant's HTC Vive Pro HMD and Vive Wireless configuration (P). An HTC Vive Wireless sensor (W) is placed at one end of the room to enable complete line-of-sight with the HMD regardless of its current location.

An *HTC Vive Pro* was used during the development and evaluation of the virtual simulation. The *HTC Vive Pro* features a visible field-of-view (FOV) of 98° horizontally and 98° vertically with a reported resolution of 1440x1600 pixels/eye. The simulation was transmitted to the *HTC Vive Pro* at a near-constant frame rate of 90Hz with *SteamVR* as the runtime environment and a *Vive Wireless Adaptor* to enable wireless data transfer between the HMD and *Unity3D* engine. To enable position and rotation tracking, four *HTC Base Stations* were set up on tripods around the laboratory and arranged so that the HMD was always in sight of at least one Base Station (Fig. 2).

To enhance user safety, A virtual grid barrier appears when participants approach the edges of the traversable space. The barrier affords a 0.5m buffer distance away from real-world objects, allowing participants flexibility in their movements.

5 STATIC ROAD-CROSSING ENVIRONMENT

The static domain environment reflects a modified version of a typical suburban American residential road, roadside, and background streetscape, but does not exactly recreate any specific street zebra crossing. The environment features a 5.5m wide bi-directional 2-lane road with a 5.5m by 5m zebra crossing placed in the middle of the road. Each lane is 2.75m wide (common design specifications for the United States) and 150m long, and the road does not feature road markings outside of the zebra crossing. (We note that there is 1:1 distance-parity between the dimensions of our physical environment for mobile VR and the simulated environment, at least for the portions of the VR that are accessible to users, i.e., apples-to-apples mapping between real and virtual in terms of absolute and traversable space.) Sidewalk segments reflect the segmented nature of sidewalks typically found in American urban/suburban settings and are coupled with low-poly building meshes to convey that situational presence as geography. To add obstacles that realistically obstruct the participants' view of the road, trees were added at 20m intervals along both sidewalks except around the crosswalk area. At the crossing roadside, traffic poles were placed on the right side of each end of the crosswalk. A partially cloudy skybox was chosen to improve immersion and lighting effects (primarily to produce shadowing effects) were baked into the environment, removing the need to add dynamic lighting effects to the simulation.

Instead of aiming for a realistic-appearing environment through high-resolution textures, the virtual simulation uses low polygonal mesh designs for buildings, vehicles, pedestrians, and trees. Buildings and trees were procured from https://poly.pizza/ and vehicle and pedestrian models were sourced from the *Unity Asset Store*. The decision to use a low-poly style was informed by a desire to reduce the "uncanny valley" effect that sometimes occurs with high-fidelity graphics [Mori et al. 2012; Schwind et al. 2018].

6 DYNAMIC ELEMENTS

Many of the dynamic systems employed in the simulation are stochastic in nature. This was a design decision that was motivated

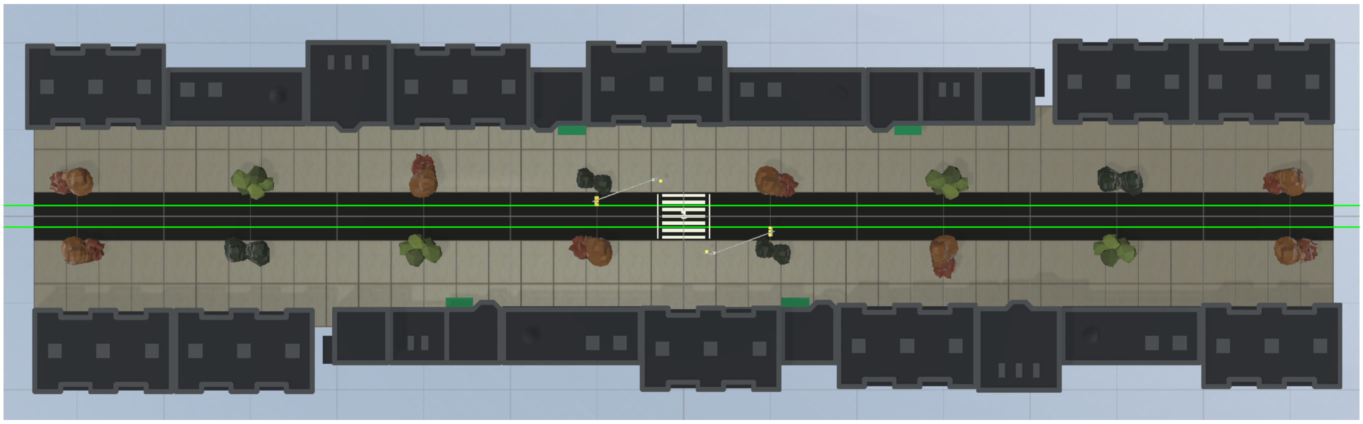

Fig. 3. Overview of static environment and relative placement of virtual obstacles. Yellow lines represent the paths that vehicles will follow and are not visible in the simulation. The rows of buildings on each side are diagonally mirrored to each other, giving participants the same static background regardless of crossing direction.

by our desire to produce dynamics of graphical objects that would appear to the user as being "organic", i.e., with plausible matches to things that they may have experiences with in their everyday walking. Presenting users with repetitive behaviors, we felt, would break some of the illusion that they were reacting with a realistic simulation of real-world conditions. To introduce pseudo-randomized behavior in dynamic agents, we used mathematical models and weighed random number generation. This was achieved via four specific subsystems:

- **Vehicular Agents**: Virtual vehicles that move along the road and accelerate/decelerate according to a microscopic traffic flow model called the Intelligent Driver Model.
- **Traffic Signals**: Pairs of traffic signals for both vehicles and pedestrians that are coordinated to switch between states at set intervals.
- **Agent-Pedestrians**: Virtual pedestrians placed in the virtual environment alongside the participant and who follow a behavioral tree to determine when to cross the road without getting struck by vehicles.
- **Ego-Agent**: A user-controlled avatar reference to the participant, placed in the virtual environment and dynamically updated to match the coordinates of the user in the tangible space of our lab settings. The ego-agent is under user control and is not subject to stochastic effects.

6.1 Vehicular Agents

"Vehicular agents" (hereafter referred to as "vehicles") are cars, trucks, and buses that the system will spawn in the virtual environment along simulated roads. Once instantiated in the simulation, vehicles travel down modeled road lanes and past the user crossing to simulate urban traffic conditions. A total of twenty distinct types of vehicles are used throughout the simulation, and they may be spawned with flexible traffic density conditions that are user-specified, e.g., free-flowing traffic, traffic waves and surges, congestion and grid-lock, etc. Although, in most experiments we spawned them randomly as users underwent multiple-trial tasks in their participation in the VR.

6.1.1 Vehicle Profiles. Vehicles were instantiated in 5 sub-classes: **"Car"**, **"Jeep"**, **"MicroBus"**, **"Sedan"**, and **"Truck"**. These types were designed primarily to establish vehicles of varying appearance, but also to accommodate a representative sample of real-world vehicle lengths and heights: these latter conditions can be important for pedestrian decisions about gap acceptance and crossing decisions. Five vehicles represent each sub-class, except for four Jeep vehicles and one Truck vehicle. Each vehicle features a different frame mesh, frame color, wheel type, and sound profile. Vehicle mesh designs were chosen to replicate a realistic variety of vehicles found in real-world urban streets. To increase realism, vehicle wheels are animated to rotate based on the current speed of a vehicle. See Fig. 5 for an overview of vehicle profiles.

In simulation. each vehicle was designed to emit a sound effect that replicates engine noises typical in the real world. Sound effects are unique to each vehicle sub-class and are spatialized, local to the current position of each vehicle. This allows for 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. This also permits us to make use of the *HTC Vive* spatial audio functions that are available on its HMD, which we availed of to create senses of audio localization in the simulation.

6.1.2 Vehicle Movement Model. Most existing car models for animations with virtual humans have focused on developing realism in vehicle traffic, i.e., by focusing on the patterns of congestion and waves of movement that emerge from local interactions among vehicles. Examples include the AutonoVI-Sim [Best et al. 2018] and CARLA [Dosovitskiy et al. 2017]. By contrast, for our applications which aim to build authentic ground-level scenarios for road-crossing experiments, we require vehicle models that are focused not only on vehicle-vehicle interactions over hyper-local distances of the road-sidewalk interface, but also vehicles models that can interplay

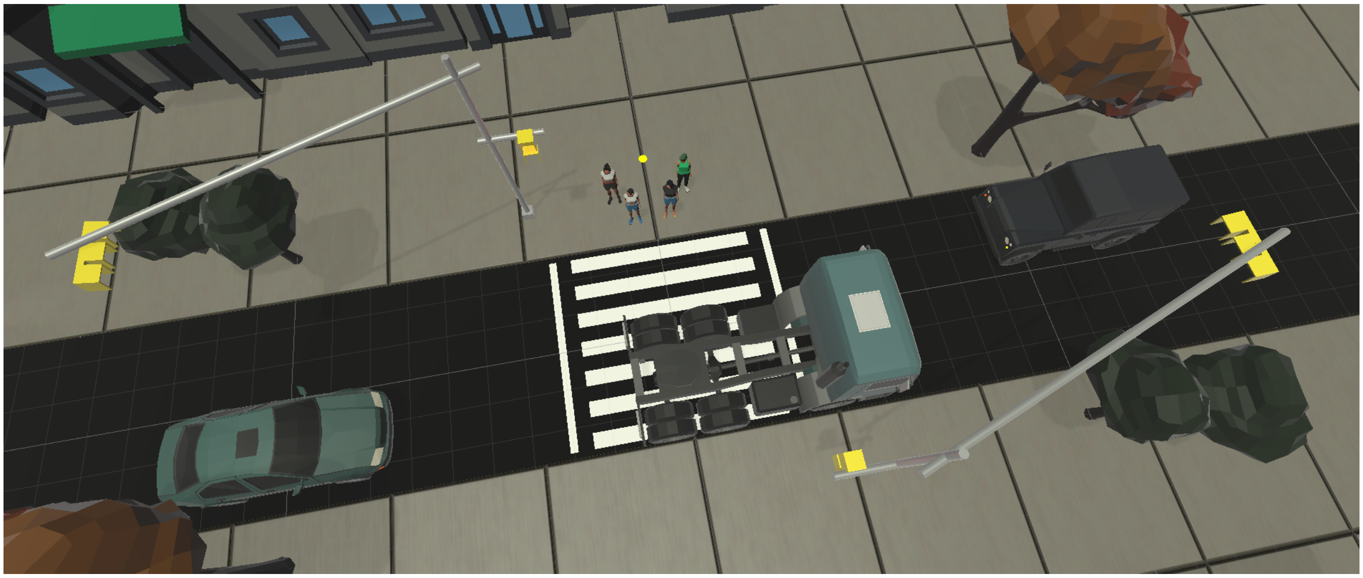

Fig. 4. All dynamic entities in one scene, with vehicles moving along road lanes, agent-pedestrians waiting for an opportunity to cross, and traffic signals allowing vehicles to go first. Ego-agents are placed approximately around the yellow dot behind agent-pedestrians at the beginning of each road-crossing scenario.

directly with pedestrians and with traffic signals. To achieve this, we built functionality that would permit vehicles, pedestrians, and traffic signals to work together with parity of exchange.

Vehicle movements in our simulation follow our own modified version of the Intelligent Driver Model (IDM) originally proposed by Treiber, Hennecke and Helbing in 2000 [Treiber et al. 2000], and extended in [Kesting et al. 2010]. IDM addresses vehicle control by attempting to mimic key axes of influence that drivers can exert in close-form traffic as a response to road conditions as they unfold around them. Chiefly, the model treats (individually and autonomously) for the preferred velocity of motion, manageable acceleration and deceleration to adjust to that preference, as well as management of preferred temporal spacing between the driver car and surrounding vehicles (i.e., minimum time headway) [Kesting et al. 2010, p. 4585]. Our simulator's implementation of the IDM model has been specifically adjusted to embody complex behavior in vehicles through interactions with objects beyond header vehicles and through weighted randomization of vehicles' target velocities. For any i^{th}, vehicle active on the 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 follows, according to the original IDM model:

$$a_i(t) = a_{max}[1 - (\frac{v_i(t)}{v_{targ}})^{\delta} - (\frac{S_{opt}}{\Delta p})^2] \quad (1)$$

Four hyperparameters in the original IDM model demand special attention:

- Δv: the difference in velocity between the i^{th} and $h(i)^{th}$ vehicles.
- Δp: the headway distance (in time and space) between the front of the i^{th} vehicle 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^{th} vehicle targets and is capped at.

Except for v_{targ}, which is a constant value, these hyperparameters only take interactions with the $h(i)^{th}$ vehicle into account. Therefore, the IDM model has to be modified to account for additional factors such as the status of an upcoming traffic signal. To this point, several new parameters are introduced:

- S_{max}: A "maximum distance" threshold parameter, unique to each i^{th} 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 (Eq. 2).
- δ_{ps}: A Kronecker delta variable that observes whether a header obstacle or vehicle exists based on S_{max} (Eq. 3).
- p_l: the position of an upcoming traffic light signal in world space.

$$\delta_L = \begin{cases} 0, & \text{if } signal == \text{"Go"} \\ 1, & \text{otherwise} \end{cases} \quad (2)$$

$$\delta_{PS} = \begin{cases} 0, & \text{if } \Delta p > S_{max} \\ 1, & \text{otherwise} \end{cases} \quad (3)$$

These new parameters are utilized in modified versions of the original Δv, Δ_p, and S_{opt} hyperparameters of the IDM model, producing a new IDM model. The modified hyperparameter equations are defined as follows:

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

Table 1. Vehicle parameters programmatically determined upon spawn

Parameter	Description	Value
v_{args}	The greatest speed the vehicle can move	Weighted random value, ranged (5m/s - 15m/s)
S_{min}	Minimal desired distance to $h(i)$	Unweighted random value, ranged (0.25m - 0.75m)
S_{max}	Distance threshold to determine if an obstacle is ahead of the vehicle	6m, constant
T_{pref}	Desired time to move forward with current speed	Unweighted random value, range (0.25s, 0.75s)
a_{max}	Maximum level of possible acceleration	$10m/s^2$, constant

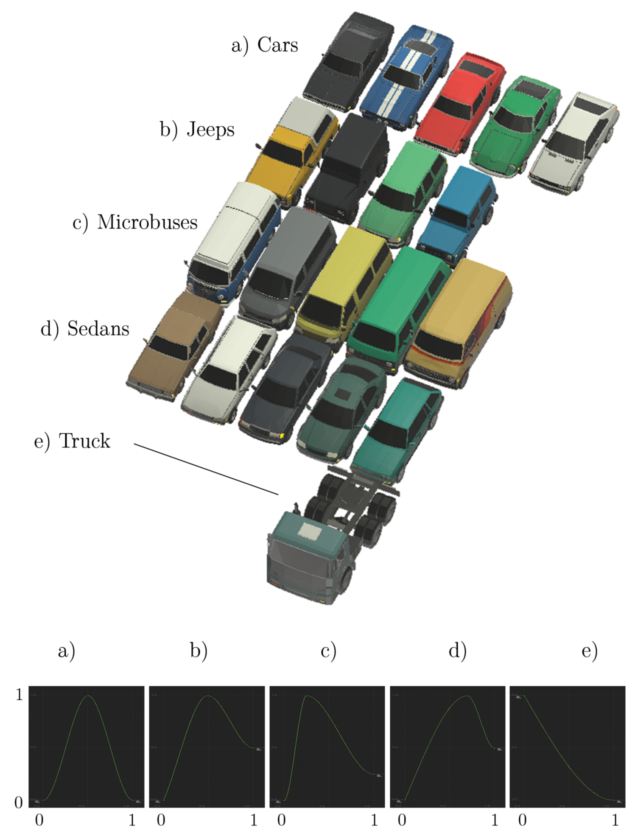

Fig. 5. Vehicle models used in the simulation, divided by subtype. Each subtype's velocity is weighted randomly by distributions between 0 and 1. Distribution curves are hard-coded but open to modification using real-world metrics in future implementations.

$$\Delta p = \delta_{PS}[p_{h(i)} - p_i(t) - length_{h(i)}] + (1 - \delta_{PS})[\delta_L(p_l - p_i(t)) + (1 - \delta_L)(S_{max})] \tag{5}$$

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

These new modifications allow vehicles to determine their acceleration relative to an upcoming signal light's state or obstacles in front of the vehicle. Should there be a red light, for example, the leading vehicle in a platoon must stop before crossing the threshold of the crosswalk while follower vehicles in the same platoon will still be dependent on the leading vehicle in front of them due to the S_{max} threshold and δ_{ps} Kronecker delta metric.

The fourth hyperparameter of the original IDM model, v_{targ}, is a key opportunity for us to create embodiment of complex behavior within vehicles from the observer's perspective such as impromptu platoon formation and speeding behavior. In particular, our simulation programmatically generates a unique v_{targ} value for each vehicle spawned through weighted random number generation. Weights are specific to vehicle subtype and represented as a distribution between 0 and 1, skewed to fit expectations regarding vehicle type and size in the real world (Fig. 5). For example, Trucks and Microbuses will feature a weight distribution that is skewed to 0, producing speeds closer to the lower bound of possible speeds.

This weighted randomization allows for the formation of platoons and speeding cars, which has been rarely explored in VR pedestrian simulators prior. Speed variations force platoons to form if speeds vary between leading and following vehicles and may occasionally introduce vehicles that go beyond participants' expectations for how vehicles may normally move. These variations are common in urban settings that experience small surges and jamming of traffic (leading to non-equilibrium through so-called "freezing by heating" effects known in dynamical and complex systems [Helbing et al. 2000b; Stanley 2000]) and can be modified through adjustment of the weight distributions to better accommodate cultural traffic behaviors. Because our simulation can generate these conditions "organically", we actually dispensed with "pre-seeding" the model to particular traffic conditions (although this is also possible shouyld a user wish to experiment with pedestrian behavior relative to traffic initial conditions).

6.1.3 Vehicle Spawning and Platoon Formation. The virtual environment limits the number of active vehicles by controlling their spawn rate, only spawning vehicles on a randomly-assigned road at intervals, as long as the number of active vehicles does not exceed the total number of vehicles allowed. For the purposes of the simulation, the vehicle number limit was manually set to 8 active vehicles at all times (which is what we have observed in prior fieldwork as roughly the maximum number of cars that a pedestrian would need to contend with in a crossing scenario ahead of them).

To encourage platoon formation between vehicles, vehicles are spawned in groups of three with a random time 1-2 seconds between each consecutive vehicle. After the group is spawned, a longer delay time of 7.5 seconds is set to create gaps between platoons. At least one platoon will form among the group of three vehicles since

```
Awake():
    Shuffle vehicle spawn order
    Let:
        w = 0
        V_{active} = [ ]
        Vqueue = [ ]
        // Vqueue(i) denotes vehicle
        //      in Vqueue at index i

Update Thread():
    If |Vactive| + |Vqueue| < 8:
        vq = next inactive vehicle
        Set random lane to vq
        Insert vq into Vqueue

Coroutine Thread():
    If |Vqueue| > 0:
        vnew = Vqueue.pop()
        Spawn vnew into its assigned lane
        if w < 3:
            wait(rand(1.0,2.0))
            w++
        else:
            wait(7.5)
            w = 0
```

Fig. 6. Pseudocode for spawning vehicle behavior during the simulation. Cars are instantiated in groups of three, each set to a random lane. The likelihood of a platoon forming is dependent on how similar the velocities of each vehicle within this set of three cars are and which cars are placed in the same lane.

vehicles are assigned a random lane when spawned and the chance of one lane being selected over the other is 50%. Vehicles will not spawn if either the number of active vehicles in the scene is equal to or greater than 8 vehicles or if the spawn points for lanes are occupied by vehicles, which often occurs if a line of vehicles is waiting for the traffic signal to turn green. Refer to Fig. 6 for a visual description of the vehicle spawn logic.

6.1.4 Interactions with Crossing Signals and Agent-Pedestrians. When a vehicle is spawned into the virtual environment, it is provided a starting point, a target destination, and (if in proximity to a crossing junction also) a traffic signal. Based on the modified IDM model, the vehicle will move towards the destination target while checking for any vehicles that are ahead of the vehicle through Unity's *Physics.Raycast()*. The vehicle will alter its acceleration based on certain 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.

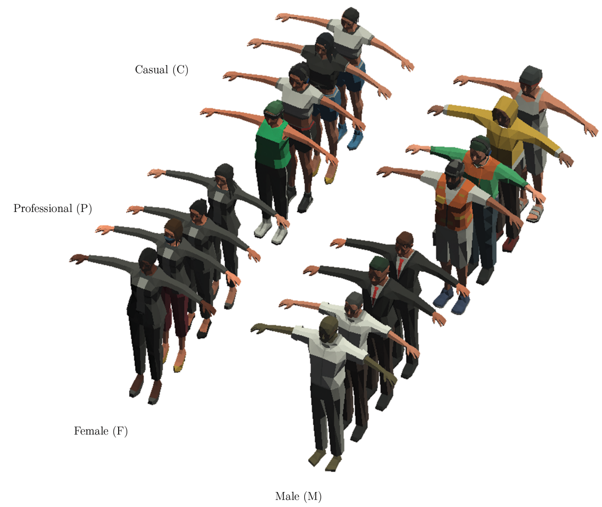

Fig. 7. Agent-pedestrians used in the simulation. Agent-pedestrians are modeled based on professionalism ("Casual", "Professional") and demographic ("Female", "Male").

- 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 despawn upon reaching it.

Importantly, we note that vehicles *will not stop* to prevent impact with agent-pedestrians and the participant. The *Collider* components between vehicles and agent-pedestrians do not detect one another, which may produce odd behavior in the simulation if an agent-pedestrian were to be "hit" by a vehicle. However, vehicle *Colliders* can collide with the participant's *Collider* and will produce a game-over scenario for participants. 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].

6.2 Agent-Pedestrians

Sixteen variations of agent-pedestrians are used and can be divided into four subtypes: **Male / Professional**, **Male / Casual**, **Female / Professional**, and **Female / Casual**, with four agent-pedestrians within each subtype. The behavior of agent-pedestrians is generated in simulation run-time using a behavioral tree that transitions an agent-pedestrian between four different states: *"Idle"*, *"Walking"*, *"Body Turning"*, and *"Head Turning"*. In this way it provides for two essential visual signs of agency that users would encounter from real-world pedestrians: locomotion signals and non-verbal communications from gesturing and attentive gaze. These states affect three subsystems that define an agent-pedestrian's behavior: **high-level navigation**, **low-level decision-making**, and **state-based animations**. Only the **visual appearance** of each agent-pedestrian is predefined and does not change across simulation scenarios.

6.2.1 Visual Appearance of Agent-Pedestrians. Each agent-pedestrian was instantiated with a customized mesh to reflect different characteristics. We introduced variation along two axes to evaluate participants' social interaction propensity for social demographics and appearance. Specifically, agent-pedestrians were designed with differences in stereotypical **professionalism** ("Professional", "Casual") and **demographic** ("Male", "Female"). For example, in simulation, professional agents were typically rendered as wearing either suits or white suit shirts, whereas casual agents typically wear short pants, t-shirts, and sweaters. Some agent-pedestrians are fitted with accessories such as headphones, face masks, or glasses.

6.2.2 State-Based Animation. To simulate realistic movements in agent-pedestrians, agent-pedestrians were animated through motion blending [Kovar and Gleicher 2003c] controlled by transitions between each agent-pedestrians' current state. We used *Unity*'s *Mecanim Animation System* to achieve this in run-time. Transitions between states were executed based on the outcome of each agent-pedestrian's behavioral tree. In this way, the agents' simulated actions constantly shift states to account for and to react to input that they receive dynamically in the simulation. These transitions are based on pre-defined parameters; the current conditions of other active, dynamic elements in the simulation; and the agent-pedestrian's current position relative to the static environment.

- *"Idle"*: The agent-pedestrian stands still, swaying left to right slightly over time.
- *"Walking"*: The agent-pedestrian moves its legs and arms in a swaying motion reminiscent of how humans normally walk in the real world. The speed of the walking animation cycle is dependent on the agent-pedestrian's maximum speed, randomized upon being spawned in the virtual environment.
- *"Body Turning"*: The agent-pedestrian rotates its whole body while leaning slightly in the direction of the rotation.
- *"Head Turning"*: The agent-pedestrian rotates its head left and right to simulate observing the traffic for an opportunity to cross.

Animations were built with data from *Unity3D*'s existing motion capture libraries and rendered using *Unity3D*'s *Animation* system, controlled through each agent-pedestrian's *Animator* and *Third Person Character* components.

6.2.3 High-Level Navigation. When an agent-pedestrian is spawned in the virtual world, it is given a set of target positions $p \in P$ and tasked with moving through all target positions starting from p_0. At each frame, the agent-pedestrian checks if it is within 0.15m of its current target position p_{targ}. Should it be the case, the agent-pedestrian sets the next item p_{targ+1} in the target destination as its "current" target (i.e., its waypoint, nested within its larger traversal path), continuing until the agent-pedestrian reaches its final target position (i.e., its path goal). For each target position, the simulation identifies a path through all adjacent, convex polygons (by connected corridor mapping) within a set of cached horizontal mesh polygons from the agent-pedestrian's starting point to the current target position. The manner in which the system traverses through the cached mesh polygons adheres to an A* best-first heuristic [Hart et al. 1968], implemented using Unity3D's *NavMesh* system and managed by a *NavMeshSurface* component. Agent-pedestrians are fitted with a *NavMeshAgent* component which directly interacts with the navigation mesh data managed by the environment's *NavMeshSurface* for high-level pathfinding.

Navigation meshes generally have already seen use in prior research concerning movement dynamics and pathfinding in virtual agents and simulated environments in both desktop and VR settings [Hackman et al. 2019; Herumurti et al. 2017; Nelson et al. 2020; Raghothama and Meijer 2015; Rojas et al. 2014]. To ensure that agent-pedestrians do not consider the road itself as traversable with exception to the crosswalk area, the *NavMesh* system takes advantage of *Unity3D*'s inbuilt *Layer* system to filter out meshes attached to objects that are not part of the "Sidewalk", "Crosswalk", or "Building" layers.

6.2.4 Decision-Making. State and transitions between *"Idle"*, *"Walking"*, *"Body Turning"*, and *"Head Turning"* are controlled by each agent-pedestrian's behavioral tree. While high-level navigation defines the movement path between whole segments of the virtual environment, a low-level decision-making process (a local action model) comes into effect when an agent-pedestrian's path requires it to cross the road.

Figure 8 broadly explains the decision-making process each agent-pedestrian uses to determine if it is safe to cross the road. Factors that affect this process include an agent-pedestrian's **Risk Level** ("Safe", "Risky"), **Maximum Speed**, and **Delay Time** prior to crossing. Risk Level is determined based on the current scenario being played by the virtual environment, whereas Maximum Speed and Delay Time are randomized upon an agent-pedestrian being spawned in the scene. These randomizations allow for variation in agent-pedestrians' movements and overall individualizing each agent-pedestrian from each other.

A crucial step for each agent-pedestrian is the ability to decide whether it is safe for them to cross. To build behavioral authenticity for ambient pedestrians that user-participants can interact with, it is important to endow those agents with exact and routine behaviors that users would appreciate from their own crossing experiences. As we will show, many users also chose to check their own behavior in the simulation experiments against the actions of the agent-pedestrian characters. Thus, building authentic crossing behaviors becomes a critical design element, we argue, in producing a useful experimental experience in the VR. It is not enough to simply animate agent-pedestrians along a pre-defined path. For the VR experiment to convey fidelity, the agent-pedestrians need to *behave* with real perception and action relative to the conditions that unfold at the simulated roadside. For agent-pedestrians, we emphasized authentic behavior in their local action model. For example, agent-pedestrians' threshold of safety is highly dependent on Risk Level, Maximum Speed, and Delay Time. The inclusion of risk follows evidence from prospect theory [Kahneman and Tversky 1979] in social science generally, and observational evidence in road-crossing studies [Sueur et al. 2013] that specifically show that pedestrians exercise visible signs of anticipation and of caution when crossing, which can be picked up by other people around them [Harrell 1991b]. The level of both expression and uptake of that caution has been shown to be dependent on age and sex factors

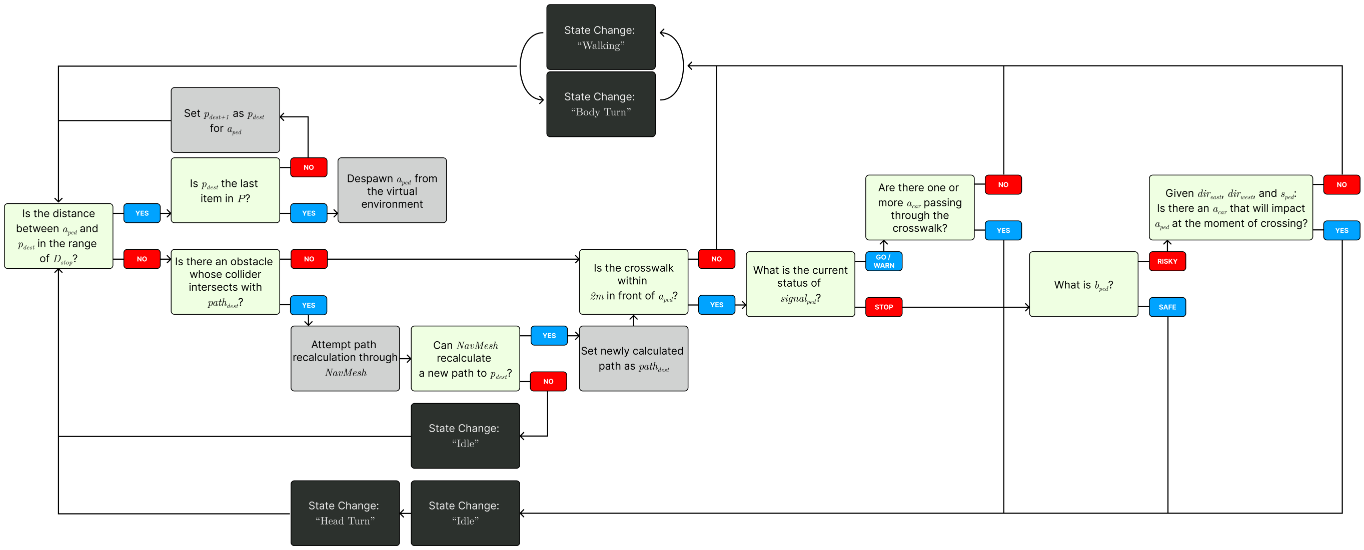

Fig. 8. Diagram depicting the behavioral tree that dictates the state of each agent-pedestrian. The behavioral tree starts from the leftmost box and flows rightward, leading into different states (black boxes). Factors extrinsic to agent-pedestrians include the current state of the traffic lights, the presence of incoming vehicles from both sides of the road, and whether obstacles are interfering with the path dictated by Unity's *NavMesh* system.

in observational studies [Underwood et al. 2007]. The notion of risk is directly relevant to how user-participants might interact with agent-pedestrians, e.g., through the personal adjustments that they make due to peer influences [Parker and Asher 1987]. A broad set of observational evidence in safety science [Liu and Tung 2014b] supports the notion 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 available crossing gaps (based on rapid assessment of the hyper-local movement of vehicles in the roadway on an allocentric basis), as well as an ego-centered check of that gap to their own sense of their abilities and the situational opportunity to proceed through the gap [Liu and Tung 2014b]. Critically, there are large variations in crossers' success in evaluating risk based on speed and delay time: young crossers do it well but overestimate the skill they have to proceed safely based on that information; 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 [Oxley et al. 2005b].

To accommodate these characteristic of virtual crossers in the VR, agent-pedestrians who play it "safe" will wait until the pedestrian crossing signal changes from "do not cross" to "safe to cross" and the traffic signals change from yellow to red. Risky agent-pedestrians on the other hand will consider it "safe" to cross if the closest incoming vehicles on each lane are at a distance from the crosswalk that is greater than a determined distance threshold. This distance threshold is unique for each agent-pedestrian and is calculated using each agent-pedestrians' Maximum Speed and Delay Time parameters. For example, an agent-pedestrian with a slower Maximum Speed and longer Delay Time will need longer gaps between vehicles than an agent-pedestrian with a faster Maximum Speed and/or shorter Delay Time.

As we will show, user-participants do demonstrate counterpart, natural behaviors in our VR simulation that map to these local action models of agent-pedestrians that they encounter, with results that seem promising in supporting experiments to test theories that could explain how those behaviors interweave into crossing scenarios. We note, in particular for example, that peer effects (even between participants and low-polygon pedestrian-agents) do actually show up in the simulation, over small and fleeting windows of exchange between the user and the crossing characters that they encounter.

6.3 Crossing Signals

In the model crossing environment, a pair of traffic signals and pedestrian signals are positioned on poles next to the zebra crossing. The behavior of these crossing signals follows a finite state machine where signals switch between **"Go"**, **"Stop"**, and **"Warn"**. We included two distinct crossing signal subtypes: **"Traffic Signals"** for vehicles and **"Pedestrian Signals"** for pedestrians. Traffic signals are located 5 meters above the road and tilted downward to allow the user's line of sight to view the current status of both traffic lights, whereas pedestrian signals are located 3 meters off the ground and located above the sidewalk area preceding both ends of the crosswalk.

6.3.1 State Transitions. Traffic signals transition between states as a result of time. A custom *TrafficSignalController* component manages how long each signal stays within its respective state. The states between both signal subtypes and their timings are listed in Table 2. These timings were based on the traffic signal transitions at a 2-lane crosswalk in front of an observation site that we established for collection of real crossing data.

Table 2. Traffic signal states and timing

Traffic Signal State	Pedestrian Signal State	Duration (seconds)
"Go" (green)	"Stop" (red)	30
"Warn" (yellow)	"Stop" (red)	3
"Stop" (red)	"Go" (light blue)	15
"Stop" (red)	"Warn" (blinking red)	30

6.4 Ego-Agent

The "ego-agent" refers to the representation of the user-participant in the virtual simulation, i.e., the manifestation of user-participant locomotion through mobile VR. In our experiments, a single user enters the virtual simulation using a VR head-mounted display (HMD) and can locomote freely within the environment through the physical movement of their head and body. The movement and rotation of the ego-agent are 1:1 mapped to the user's physical movement and do not utilize joystick options, movement acceleration, or movement multipliers. In this way, when users move in a real space (our laboratory) that movement is transposed into the VR directly [Torrens and Gu 2023]. Again, we note that we deployed mobile and wireless VR so that participants could move naturally in the experiments.

6.4.1 Self-Representation in the Simulation. Ego-agents do not have a physical avatar or other self-representation in the virtual simulation save for a yellow dot that follows underneath the player's head position and acts as an indicator for players as to where they are relative to the sidewalk and road. While prior research has indicated that the lack of self-representation makes it difficult for immersed players to understand where they are relative to other entities in the virtual environment [Koilias et al. 2020] and the existence of a self-representative avatar improves immersion [Feldstein et al. 2016], the yellow dot was implemented as a means of players to re-orient themselves if they were unsure where they were position-wise.

6.4.2 Interactions with other Entities. A *Collider* is attached to the ego-agent's virtual "head", enabling collision events to occur between the ego-agent and vehicles active on the road. All *Collider* components attached to vehicles are set such that they will hit the ego-agent's *Collider* regardless of the user's height in the real world. No collision interactions were implemented between the ego-agent and agent-pedestrians. This design decision was made to ensure that any movement behavior from user-participants could be isolated to crossing.

7 EVALUATING THE SIMULATION

To evaluate the VR simulation's ability to entice users to embody real-world attributes to virtual elements and induce real-world street-crossing strategies, we conducted a live, multi-session within-subjects human behavioral study with 24 recruited participants. Participants were subject to 36 street-crossing scenarios and a series of pre- and post-study questionnaires as well as a semi-structured interviews about their real-world and virtual street-crossing experiences. Approval for the study was obtained from the Institutional Review Board at our home institution. We note that the study ultimately involved a total of 22 x 36 (792) actual experiments, with a large volume of data collected for each, and with full records of the tangible behavior of the participants in our lab as well as the complete graphical models of their run-time in the simulation system. In short, while the recruitment cohort was modest, we collected a *huge* amount of empirical data.

7.1 Participants

24 individuals (9F, 15M) participated in this evaluation. Results from two participants (M) were removed from the post-hoc evaluation due to hardware complications that prevented reliable data collection. Data from a total of 22 participants were recorded and anonymized. No participants reported problems in the experiments due to Simulator Sickness.

Participants were recruited through a public recruitment campaign with posters and by physically approaching potential participants using snowball sampling. Participation was limited to individuals who had lived in the city where the user study took place for at least six months and regularly navigated streets while they resided there. Each participant was compensated a $5 gift card for participating in the study.

7.2 Experimental Conditions

Participants were introduced to 36 road-crossing scenarios in the virtual environment through the *HTC Vive Pro* HMD. Each scenario depicted a different assortment of virtual agent-pedestrians based on the following combinations:

- Number of agent-pedestrians crossing the street alongside the ego-agent (0, 1, 4)
- Visual attire of agent-pedestrians (Professional, Casual, Mixture*)
- Demographic of agent-pedestrians (Male, Female, Mixture*)
- Risk behavior of agent-pedestrians ("Safe", "Risky", Mixture*)

** Mixed cases only occur in scenarios with 4 agent-pedestrians present. For example, a group of four agent-pedestrians mixed in visual sex but all professionally clothed will have two Male and two Female agent-pedestrians in suitwear.*

Although the simulation allows for the introduction of set patterns of traffic (free-flow, congestion, tailgating, etc.), in the user experiments, we did not specify any particular patterns per crossing scenario due to the intentional implementation of unpredictability in the car spawn and movement logic. No variations were made to the number of cars or timing of traffic lights due to the randomized nature of car-spawning logic. 36 scenarios were believed to be sufficient enough to observe participants' behavior toward vehicles. Examining user crossing relative to set and hyper-local traffic patterns (temporary congestion, blocking of crosswalks, turning dynamics at red lights, etc.) is a topic for future investigation. As we mentioned earlier, our stochastic components generated realistic-appearing formations of traffic without the need for parameterization of initial conditions, although the system is still open to doing so.

Experimental conditions were split into two sessions of 18 experimental trials with an additional 3 dummy trial conditions added to the beginning of each session to reduce the effect of novelty bias, totaling 42 trials across two experimental sessions. A two-minute resting period was enforced between sessions to give participants

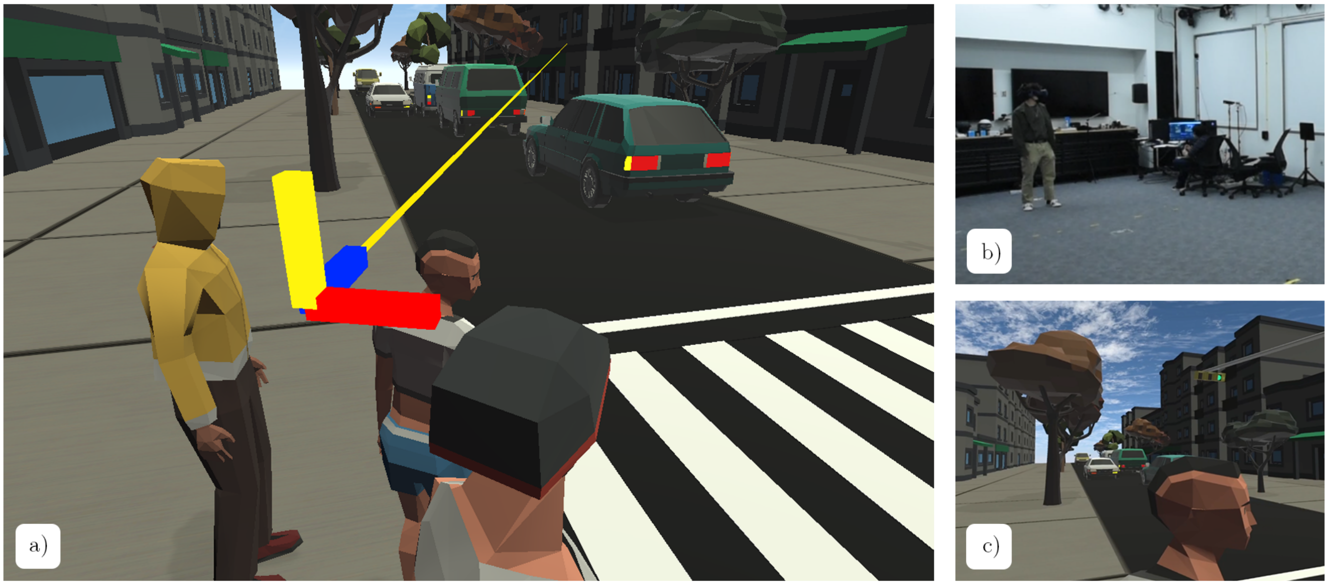

Fig. 9. A moment in time during a user study, captured across three separate dimensions, Fig. a) depicts a screenshot of the scene from a 3rd-person camera and a yellow line representing the participant's head orientation. Fig. b) is the same participant in the real world, wearing an HTC Vive Pro headset. Fig. c) shows the same scene but from the participant's viewpoint. The participant looks past the other agent-pedestrians to observe for approaching vehicles

time to rest from the first session, and this resting period was extended if needed on a case-by-case basis.

7.3 Data Collection

Demographic, subjective, and empirical data were aggregated from participants during the course of the evaluation. Demographic data was collected either as part of a pre-study online survey, which was widely distributed through posters and word-of-mouth, or during post-study, semi-structured interviews with participants. Subjective data regarding participants' experience in the simulation were collected by both a post-study online questionnaire and the same aforementioned semi-structured interview, both taken immediately after each participant's experimental trials. Empirical metrics were recorded digitally through Unity3D using a set of data listeners [Liu and Tung 2014b], and later post-processed to generate findings.

7.3.1 Demographic Metrics. Demographic data collected from participants include:

- Participants' stated sex.
- Participants' age (in years).
- Whether participants obtained a driver's license or close equivalent (e.g., a driver's permit).
- Participants' previous experience with directly (not through social media or television) witnessing pedestrian-related accidents.
- Participants' previous experience with directly being involved in one or more pedestrian-related accidents.

7.3.2 Subjective Metrics. Subjective data includes participants' attitudes towards:

- **Presence**: the feeling of "being there", acting as an agent within the VRE as opposed to being just an outside onlooker, through the participant's actions in the VRE to effect tangible changes in the VRE, as well as through users' sense that events that transpire in the VRE have an effect on the participant.
- **Exactness**: the feeling that the VRE depicts events and behaviors in entities that match known experiences in the real world.
- **Task Load**: feelings such as frustration, mental stress, physical stress, and discomfort that may be felt during the course of the experiment.

In the post-study interview, participants were also broadly asked about the following:

- **Overall impressions of the simulation**: any immediate thoughts, things they noticed, negative or positive sentiments.
- **Incorporating real-world strategies**: whether participants were able to apply their real-world road crossing strategies towards the simulated scenarios. This also covered the question of whether there were any obstacles or inconsistencies with the real world that prevented this from happening.
- **Oddities**: whether there was unusual behavior in the way the vehicles, agent-pedestrians, or traffic light system acted. This addressed issues of whether the VRE itself had any unusual (i.e., outside quotidian experience) qualities.

While the complete transcripts of these interviews will not be reported on in the Results section, findings from them will color aspects of the VRE mentioned in the Discussion section of this paper.

7.3.3 Empirical Metrics. During the course of each participant's experimental trials (as well as during post-processing of trial data), the following metrics were recorded. **Bolded** metrics are reported and discussed in the Results section.

Tracked during each trial at 0.05-second intervals (approximately every 4 frames/second):

- Position and rotation of the participant's head in the VRE;
- Position and rotation of all vehicles and agent-pedestrians;
- Gaze direction and target, based on the participant's head orientation.

Tracked asynchronous to frame rate of the simulation:

- **Time to completion for each trial**;
- **Number of failed attempts to cross the road**, including the participant's as well as each agent-pedestrian's attempts. Attempts are labeled as either being successful or not successful based on whether the participant or agent has either (1) returned to the starting sidewalk (a failed attempt), (2) collided with a vehicle (a failed attempt), or (3) whether the participant or agent has managed to reach the other sidewalk (a successful attempt);
- Timestamps for when a vehicle has crossed the center line of a crosswalk.

Calculated during post-processing:

- **Number of rejected gaps ("naive", "filtered") for each participant**. "Naive" gaps are all gaps between vehicles that passed (lapsed without being used for a crossing attempt) 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. Keeping a metric regarding filtered gaps ensures that smaller, impossible gaps such as those between cars in platoons are not captured in the data.

To collect the data needed for empirical analysis, the position and rotation of the participant's virtual head, all vehicles active in the scene, and virtual agents are tracked at 0.05-second intervals (approximately every 4 frames/sec). This time loop was intentionally chosen over an every-frame tracking system in order to prevent the simulation from lagging due to excessive memory use.

7.4 Procedure

7.4.1 Recruitment and Pre-Study Demographic Data Collection. Prior to the study, potential participants answered a pre-study survey inquiring about demographic characteristics, prior experience with VR, and real-world experience crossing streets in the city where the user study took place. Upon completion of the pre-study and enrollment in the study, participants were invited to visit our laboratory to engage in the experiments. Experiments were limited to single participants, all experiments were 1:1 sessions between the participant and experimenter. Participants completed a consent agreement with information about the study and assurances about the intended use of the study results and data, as overseen by a Human Subjects protocol with our Institutional Review Board (IRB). For each experiment, we collected (by consent) film and audio recorded during the user sessions. In this way, we have matched records of both the experiments' progression within VR, as well as the real and tangible actions of participants in the laboratory. Once the consent agreement was signed, the participant was transposed into the virtual street through the *HTC Vive Pro*. We note that we used a *wireless* HMD, so that users had relative freedom to move and look around in the VR without constraint. Adjustments were made to the HMD to better accommodate the comfort and fit with the participants' head shape.

7.4.2 Training Session. A brief training session was conducted where the experimenter could inquire about any potential lag, graphic anomalies, or misalignment between real-world and virtual movement speeds and the participant had a chance to explore the VRE. During the course of this training session, the experimenter walked alongside the participant to ensure that they would not collide with anything in the lab environment (chiefly, walls). The sequence of tasks for the training period was as follows:

(1) Have the participant rotate their head around and comment on any rotation-based lag or graphic distortion.
(2) The participant was told to physically take 5 steps forward to one of the extremes of the traversable area; participants were asked to comment on any lag or graphic distortions during this movement. Upon reaching the edges of the traversable area and seeing the safety barrier, the participant was informed about the nature of the barrier and when it would appear during the simulation.
(3) The participant was then rotated 180° and told to take 10 steps forward; participants were asked to comment on any lag or graphic distortions during this movement and rotation.
(4) The participant was then asked if they experienced any form of nausea, dizziness, or excessive fatigue during the training session.

7.4.3 Experimental Trials. After the training session, participants were informed that they would be proceeding to the actual experiment and were explicitly instructed on the following:

(1) The primary task of participants was to **cross to the other side of the road as they would in the real world**.
(2) Participants could move around anywhere in the VRE as long as it was within the traversable bounds demarcated by the safety grid barrier.
(3) The experiment would be divided into 10-minute sessions where participants would engage in their task across different scenarios, with 1-2 minute breaks in between. Participants were encouraged to move at their own pace*.
(4) If participants experienced any form of nausea, dizziness, vertigo, or excessive fatigue they must verbally report these symptoms to the experimenter, who would then disable the simulation to allow a recuperation period.

** While a set number of scenarios was pre-fabricated, this was not explicitly mentioned to participants to avoid encouraging participants to anticipate the end of the experiment and therefore alter their behavior in response (e.g., moving faster than usual to finish the experiment in a hurry).*

After verbally confirming the participants' understanding of the instructions, the experimenter would then randomize the order of trials to prevent early biases in data and initialize the first 10-minute session. Between each session, participants would be told to take off the HMD and sit down while the experimenter confirmed the current number of trials the participant completed during the first session. After at least one minute, the experimenter informed the participant to prepare for the second session by putting the HMD on again. Participants would be run through the training session again to affirm that no lag, glitches, or negative symptoms appeared. The second session would start immediately once the training period ended.

During the experiment, an experimenter would observe participants' actions through a pass-through video feed depicting the current POV of the participant in the virtual simulation. The computer screen and experimenter were positioned such that the participant was always in view of the experimenter. The experimenter would simultaneously take notes during the study by hand and note any unique behaviors participants performed during both sessions. (Again, we note that we also recorded video of the entire laboratory for review after the experiments if necessary.)

7.4.4 Post-Experiment Questionnaire and Interview. After all experimental sessions were completed, participants were instructed to take off the HMD and take 5-10 minutes to complete a post-study questionnaire asking about their experiences in the VR simulation. A 20-30 minute interview was conducted afterward to assess participants' subjective experiences in the VR simulation, clarify details about unique behaviors noted by the experimenter during the trial, and gain context about each participant's real-world street-crossing behavior. Interviews were semi-structured, following a broad organizational outline but otherwise giving participants and the experimenter the freedom to discuss deeper about certain topics, ideas, or suggestions for improving the simulation.

8 RESULTS

8.1 Presence, Realism, and Task Load

After participants completed their tasks in the VRE, they were required to answer 21 questions pertaining to (1) their feelings of presence, (2) the realism of the VRE, and (3) their experience with task load. These questions were asked in the post-study questionnaire through Likert-scale inquiries whose answers ranged between 1 (negative sentiment) and 7 (positive sentiment). Questions pertaining to Presence were adapted from the iGroup Presence Questionnaire (IPQ) by Schubert et al. [Schubert et al. 2001] due to some of its questions demonstrating high inter-correlation with other popular presence questionnaires [Schwind et al. 2019] such as Wittmer and Singer's Presence Questionnaire [Witmer and Singer 1998] and Slater, Steeds, and Usoh's questionnaire [Usoh et al. 2000]. Task load questions were adapted from Nasa's Task Load Index [Hart and Staveland 1988]. To avoid biasing participants into skewing responses to one side, questions were modified so that the questionnaire contained both positive and negative-toned questions (e.g., **P7**: "I was focused towards trying to pay attention to the real-world environment").

Table 3. Post Survey Questionnaire Likert Scale Statistics

Q. ID	Q. Sentiment	Means	Medians	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

Responses to these questions across all participants are visualized in Fig. 12 with additional metrics presented in Table 3.

8.1.1 Presence Questions. Questions P1 to P11 asked participants about their feelings of Presence as it pertains to the virtual environment. These questions were as follows:

(1) **P1**: In the computer-generated world I had a sense of being there.
(2) **P2**: Somehow I felt that the virtual world surrounded me.
(3) **P3**: I felt like I was just perceiving pictures.
(4) **P4**: I did not feel present in the virtual space.
(5) **P5**: I had a sense of acting in the virtual space, rather than operating something from outside.
(6) **P6**: I was aware of the real world around me while navigating in the virtual world.
(7) **P7**: I was focused towards trying to pay attention to the real-world environment.
(8) **P8**: I was completely captivated by the virtual world.
(9) **P9**: How real did the virtual world seem to you?
(10) **P10**: How much did your experience in the virtual environment seem consistent with your real world experience?
(11) **P11**: To what extent were you able to distinguish the virtual environment from the real world?

Participant answers to Presence-related questions scored relatively high, especially in regard to participant's ability to perceive the space around them as three-dimensional. Responses to questions **P3** ("I felt like I as just perceiving pictures"), **P4** ("I did not feel present in the virtual space"), **P6** ("I was aware of the real world around me while navigating in the virtual world"), and **P7** ("I was

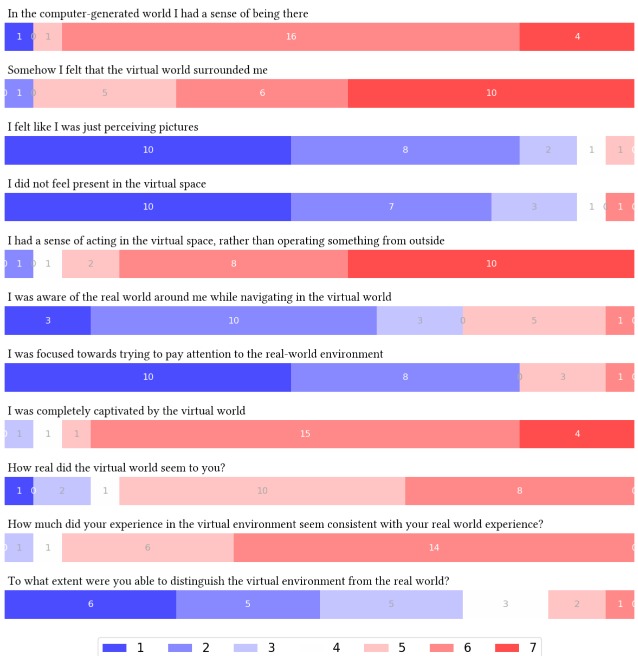

Fig. 10. Aggregated responses to questions in the "Presence" category. Note that questions **P3** ("I felt like I as just perceiving pictures"), **P4** ("I did not feel present in the virtual space"), **P6** ("I was aware of the real world around me while navigating in the virtual world"), and **P7** ("I was focused towards trying to pay attention to the real world environment") reflect negative sentiments, meaning that the substantial negative responses to those questions uphold the VRE's ability to induce feelings of Presence. Scores remain high overall despite a negative-leaning response to **P11** ("To what extent were you able to distinguish the virtual environment from the real world").

focused towards trying to pay attention to the real world environment") reflect negative sentiments, meaning that the substantial negative responses to those questions in actuality uphold the VRE's ability to induce feelings of Presence. A substantial negative response to **P11** ("To what extent were you able to distinguish the virtual environment from the real world") has been identified from interviews as a take on the VRE's visual fidelity, as most participants noted how they immediately knew it wasn't a real world from the low-poly models alone.

8.1.2 Realism. Questions R1 to R4 ask participants about their feelings of Realism as it pertains to the virtual environment. These questions are as follows:

1. **R1**: I felt compelled to behave as I would in the real world when deciding whether to cross the road in the virtual world.
2. **R2**: I felt compelled to avoid collisions with vehicles on the road.
3. **R3**: I felt compelled to avoid collisions with other pedestrians.
4. **R4**: I felt compelled to obey traffic signals when crossing the road.

Participant answers to Realism-related questions were positive-leaning for **R1** ("I felt compelled to behave as I would in the real world when deciding whether to cross the road in the virtual world") and **R2** ("I felt compelled to avoid collisions with vehicles on the road") but were more divided on **R3** ("I felt compelled to avoid collisions with other pedestrians.) and **R4** ("I felt compelled to obey traffic signals when crossing the road"). While responses to **R4** were clarified to also correlate with people's behaviors in the real world (meaning their responses here are actually how they would behave with regard to real-world traffic lights as well), responses to **R3** were largely varied. Some participants mentioned that the pedestrians "seemed realistic" in their movements, noting that they don't just appear to be running into the middle of the street, while other mentioned that the fact they would not react the participant's movement around them made them seem less real. Low scores for **R3** were generated from participants who viewed the pedestrians incredibly risky, noting that their decisions to cross when they did seemed too dangerous and too precise to the timing of vehicles. Participants who noticed this decided to no longer pay attention to the virtual agents, treating them more as visual obstacles that hindered their view of the road.

8.1.3 Task Load. Questions T1 to T6 ask participants about their experiences with Task Load as it pertains to the virtual environment. These questions are as follows:

1. **T1**: Mental Demand - On a scale between 1 (very low demand) and 7 (very high demand), how mentally demanding was the task?
2. **T2**: Physical Demand - On a scale between 1 (very low demand) and 7 (very high demand), how physically demanding was the task?
3. **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?

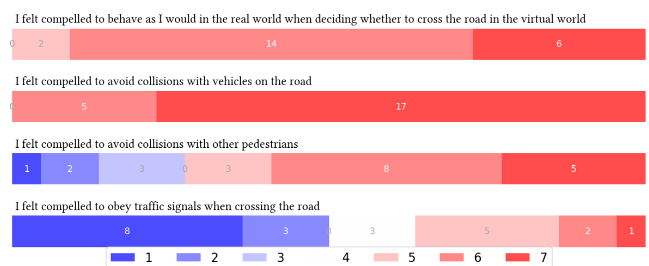

Fig. 11. Aggregated responses to questions in the "Realism" category. Responses are consistently positive for **R1** ("I felt compelled to behave as I would in the real world when deciding whether to cross the road in the virtual world.") and **R2** ("I felt compelled to avoid collisions with vehicles on the road.") but lean towards negative sentiments with **R3** ("I felt compelled to avoid collisions with other pedestrians.") and **R4** ("I felt compelled to obey traffic signals when crossing the road."). Answers to **R4** were confirmed to correlated strongly with real-world attitudes to street lights, but participants were more divided on their perceptions of agent-pedestrians

(4) **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?
(5) **T5**: Frustration - On a scale between 1 (not frustrated) and 7 (very frustrated), how insecure, discouraged, irritated, stressed, and/or annoyed were you?
(6) **T6**: Success - On a scale between 1 (unsuccessful) and 7 (successful), how successful were you in accomplishing what you were asked to do?

Responses to Task Load-related questions are largely negative, showing that participants did not feel much mental, physical, or temporal demand put onto them by the experience. We regard this as an encouraging finding. Occasional high scores for questions **T1** ("Mental Demand - On a scale between 1 (very low demand) and 7 (very high demand), how mentally demanding was the task?") correlate with participants who noted that they treat road-crossing really seriously but the limited field of view (FOV) of the HMD made it harder to view from their peripheral vision. The lack of peripheral vision contributed to other responses in this category as well, with participants noting that the fact their range of senses was limited both visually and sometimes auditorially (some participants could not hear approaching cars) meant they had to struggle to memorize the relative positions of approaching vehicles. However, participants were able to adapt to this scenario as trials continued on in their respective scenarios. High responses to question **T6** ("Success - On a scale between 1 (unsuccessful) and 7 (successful), how successful were you in accomplishing what you were asked to do?") indicate that despite some mental demand put onto participants, participants did feel like they were able to complete the task of road-crossing without much trouble. One negative sentiment in **T6** came from a participant who collided with vehicles in rapid succession initially, but this participant was able to complete the tasks nonetheless and answered close to neutral-negative.

8.2 Empirical Metrics Across Demographic Factors

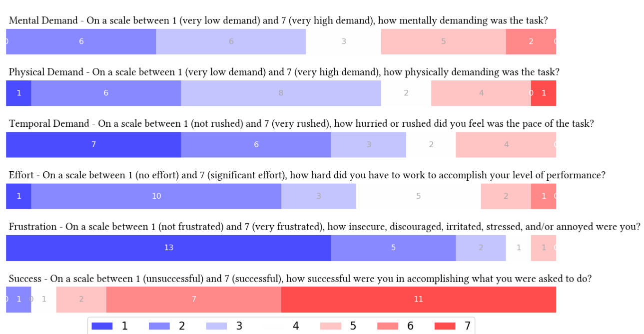

Fig. 12. Aggregated responses to questions in the "Task Load" category. Responses lean mostly to the negative, meaning that participants did not feel excessive mental, physical, or temporal demand while performing the task. Occasional high answers for questions were highlighted to be due to the act of physically moving. A strong positive sentiment in **T6** ("Success") confirmed that participants were able to complete their task without difficulty.

Table 4. 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

$\alpha = 0.05$

8.2.1 Evaluation Methods for Empirical Metrics. To observe whether a significant departure from normal trends was found across all metrics, the Shapiro-Wilk Normality Test (SWT) and Kolmogorov-Smirnov Test (KST) were conducted (see Table 4 for p-values). No significant departure for normality was found according to the SWT for **Trial Durations**, **# Rejected Gaps (Naive)**, and **# Rejected Gaps (Filtered)**, whereas the **# of Red-Light Violations**, **# Failed Attempts**, and **# Vehicle Collisions** failed the normality tests. Therefore, we are 95% confident that the data for these three specific metrics do not fit a normal distribution. Nevertheless, with the exception of these metrics, the remaining indicators of user experience are statistically viable.

Based on this, **Trial Durations**, **# Rejected Gaps (Naive)**, and **# Rejected Gaps (Filtered)** were regarded as parametric data according to the normality assumption and required either the Independent T-Test (for *Sex* and *License Ownership*) or One-Way ANOVA (for *Age Group*, *Prior witnessing of pedestrian accidents*, and *Prior involvement in pedestrian accidents*). Alternatively, the **# of Red-Light Violations**, **# Failed Attempts**, and **# Vehicle Collisions** metrics were regarded as non-parametric and required either the Mann-Whitney U Test (for *Sex* and *License Ownership*) and Kruskal-Wallis One-Way Test for Variance (for *Age Group*, *Prior witnessing of pedestrian accidents*, and *Prior involvement in pedestrian accidents*).

8.2.2 Significant Effects on Empirical Metrics. Table 5 highlights the results of statistical testing for significance across different demographic factors, with $\alpha = 0.10$ chosen as the p-value threshold. When comparing different factors among the same population, the effects of *Sex* on the **# of Red Light Violations** ($p = 0.04127$) and **Trial Duration** ($p = 0.09838$) were statistically significant. Furthermore, *License Ownership* has a statistically significant effect on **Trial Duration** as well ($p = 0.07099$). Whether someone had *Witnessed a Pedestrian-Related Accident* had a statistically significant effect on both the **# of Red-Light Violations** ($p = 0.03098$) and **# of Vehicle Collisions** ($p = 0.03532$). Lastly, Whether someone was *Involved in a Pedestrian-Related Accident* had a statistically significant effect on **# of Vehicle Collisions** ($p = 0.01834$).

8.2.3 Observing Trends in Metrics Across Factors and Time. In Figure 13, we illustrate details of the general performance of participants based on demographic factors. While it may appear to be that these figures depict patterns among factors that weren't captured during tests for significance, it must be emphasized that inter-metric count

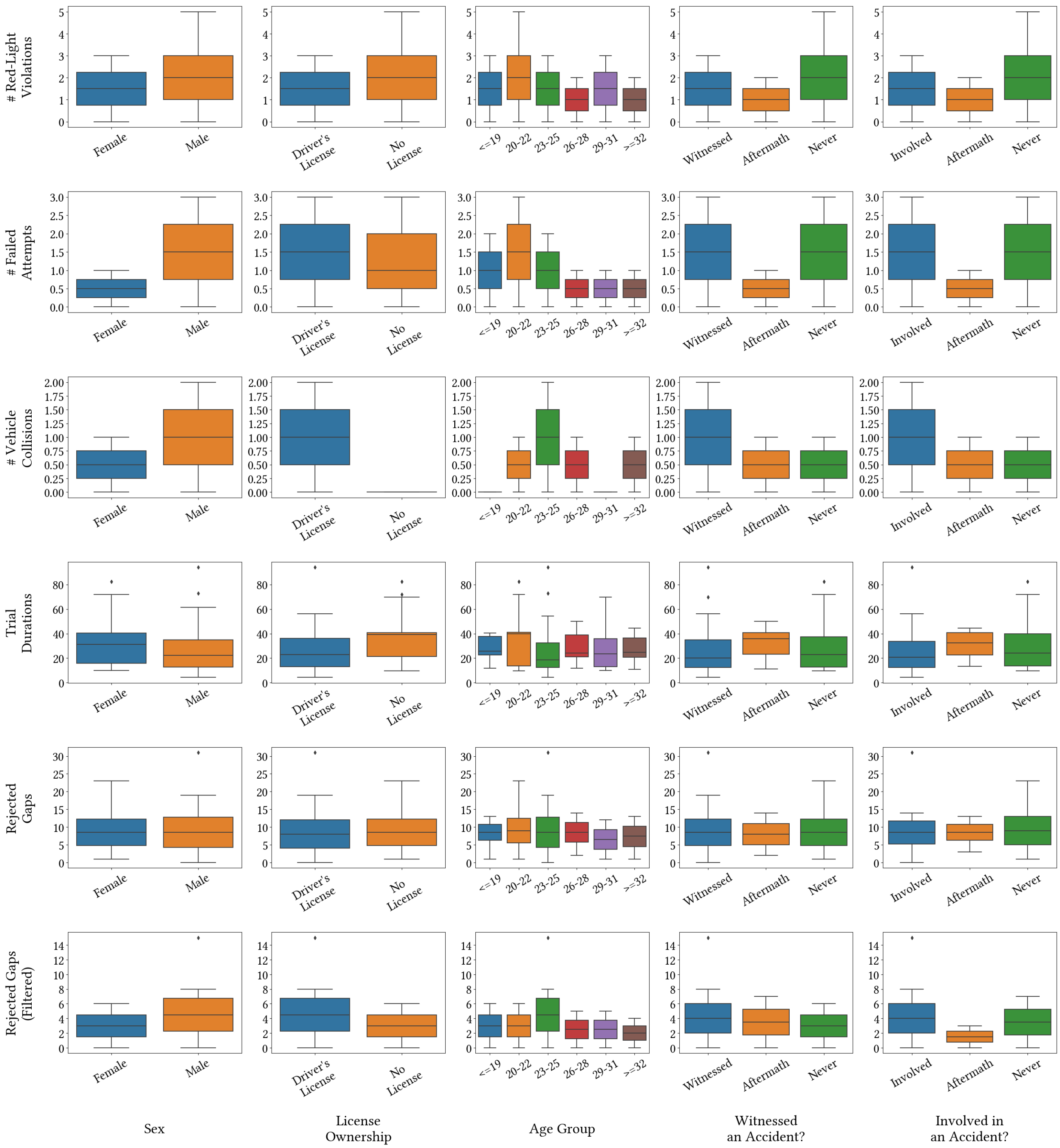

Fig. 13. Box plots that visualize, by row, the following metrics: **# of Red-Light Violations**, **# of Failed Attempts**, **# of Vehicle Collisions**, **Trial Durations**, **# of Rejected Gaps (Naive)**, and **# of Rejected Gaps (Filtered)**. Metrics are compared against 5 demographic factors, by column: *Sex*, *Driver's License Ownership*, *Age Group*, *Prior Witnessing of Pedestrian Accidents*, and *Prior Involvement in Pedestrian Accidents*.

ranges are *distinctly* different from one another and that some graphs overly emphasize differences between members of subgroups.

The aim of the paper is to examine how local action models can establish verisimilitude and fidelity for user-participants in VR (the success of which we assess in the next section). The experiments, however, did reveal some findings with substantive relevance to the theoretical domain science of crossing safety. We will discuss this again later in the paper, but we mention a few instances here simply to show the usefulness of the VR as an experimental platform. For example, our findings indicate that Male participants tend to commit more red-light violations than Female participants and often experience greater numbers and variations in failed attempts. This correlates with higher numbers of collisions with vehicles. Females generally take longer to complete trials, whereas Males' time-to-completion is skewed heavily toward shorter times. While the overall number of rejected gaps is similar across demographics, Males reject 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 behavior in the safety science literature, which shows generally riskier behavior of males, especially young men [Onelcin and Alver 2015]. We will expand on the lessons relative to domain science in the Discussion section that follows in this paper. We also found that participants that are in younger age groups in our study tend to perform more red-light violations than their older counterparts and experience more failed attempts as well. No discernable trends in time-to-completion duration as well as number of rejected gaps were found to be statistically relevant. Further, participants who have never directly witnessed a pedestrian-related accident perform more red-light violations than participants who directly witnessed them. Interestingly, those who witnessed accidents experienced more vehicle collisions than those who have not witnessed any accidents or who only saw the aftermath of accidents. A similar trend occurs among participants who have been involved in a pedestrian-related accident, versus participants who have never been involved or have been involved in the aftermath of accidents. These patterns were verified through a Kruskal-Wallis One-Way Test for Variance which determined that prior experience witnessing or being involved in accidents had an effect on vehicle collisions in the VRE.

9 DISCUSSION

9.1 Participants' Perspectives on Verisimilitude and Parity Between VR and the Real World

Overall, findings suggest that the VR simulation was able to portray an interactive experience with enough parity with real-world experiences to communicate a level of situational verisimilitude that could induce realistic actions, reaction, and interactions from user participants relative to the VR world and its assets. We validated these findings empirically against our survey data.

9.1.1 Presence and Movement Verisimilitude. High presence scores for questions in the post-study questionnaire indicate that participants felt successfully immersed in the VRE. We reported high scores for questions such as **P1** ("In the computer-generated world I had a sense of being there"), **P2** ("Somehow I felt that the virtual world surrounded me"), and **P5** ("I had a sense of acting in the virtual space, rather than operating something from outside"), alongside low scores for questions like **P3** ("I felt like I was just perceiving pictures") and **P4** ("I did not feel present in the virtual space"). These results indicate (empirically) that participants felt that they were part of (and present in) the virtual environment. It also shows that the virtual environment avoided pitfalls of feeling like a 2D representation, such as a video. And we found that the actions of participants were realistically communicated and embodied through changes in their visual stimuli, such as head tilts and micro-movements to properly rotate and translate the VR world in ways that the participants expected of pedestrians around them at crossing sites. The fact that no participants experienced SS for the duration of their experimental trials suggests that little to no visual-vestibular mismatches occurred among participants, furthering the notion that the simulator was sufficiently capable of conveying movement interactions similar to that in the real world.

Only one participant mentioned in their post-study interview that they felt their horizontal speed in the VRE felt slower than their real-world walking speed and thus they felt the need to trot at a speed faster than their normal speed. No observable metric has made it clear why this is the case for this participant, though it could be surmised that the participant's height, taller than the average height of all participants, caused visual distortion in how they perceived space.

9.1.2 Visual Verisimilitude. We reported high scores for participants' feelings of presence. This result juxtaposes, perhaps markedly, with the low score for question **P11** ("To what extent were you able

Table 5. Significance Metrics

	Sex		License Ownership		Age Group		Witnessed		Involved	
	t-value	p-value	t-value	p-value	t-value	p-value	t-value	p-value	t-value	p-value
# RLV	89.5	**0.04127**	50.0	0.17850	2.42381	0.78792	6.94903	**0.03098**	1.59298	0.45091
# Failed Atmpt	76.5	0.23144	34.0	0.96186	3.24042	0.66298	2.56222	0.27773	1.59721	0.44996
# Vehicle Col.	65.5	0.57833	50.0	0.10126	1.56074	0.90596	6.68647	**0.03532**	7.99790	**0.01834**
Trial Duration	-1.7336	**0.09838**	-1.92602	**0.07099**	0.78184	0.57731	1.49396	0.25418	0.43751	0.65314
# Rej. Gaps (Naive)	-1.6141	0.12218	-1.55654	0.13800	0.60144	0.69973	1.68767	0.21626	0.33995	0.71682
# Rej. Gaps (Filt.)	-0.9099	0.37371	-0.22349	0.82582	0.20162	0.95709	0.39845	0.67784	0.19116	0.82786

to distinguish the virtual environment from the real world"). In post-study interviews, most participants attributed a high sense of presence to the low-poly/low-res depiction of the virtual environment as a visual setting. In other words, participants largely were able to recognize that this was indeed a virtual world and not a "realistic" one as far as visual fidelity goes. Nevertheless, they felt present in the environment and connected to its assets in their behavior. Verisimilitude and fidelity are, we argue, important design channels for achieving useful experimental conditions.

We validated through post-study interviews that the low visual fidelity of the environment induced some changes in participants' attitudes towards accomplishing the goal of crossing the street. A common trend seen among some participants is that they started to interpret the simulation as if it were a video game. For example, one participant started to perceive the vehicles and pedestrians as following a strict set of static rules such as constant speeds and gap distances, leading to them move more riskily throughout their trial under the assumption that no unpredictability was built into the simulation. (Which was not actually the case.) Another participant remarked that the simulation feeling like a video game made them want to proceed through the simulation faster, believing that the simulation was secretly a human-subjects performance test to compare movement speeds between participants. A third participant also highlighted that the "cartoonish" nature of vehicles overwhelmed any sense of realism from the simulation, convincing them to take more risks than they normally would. This is, we find, an interesting result in its own right, as it points to users being pre-conditioned to thinking of VR as a form of entertainment. This could straightforwardly be countered by telling the participants that the crossing experiment is designed to inform real safety designs, or that the pedestrians in the simulation are based on data from real-world crossers, for example. Nevertheless, despite this reaction from some participants, our findings showed relatively high scores for questions **P10** ("How much did your experience in the virtual environment seem consistent with your real world experience?"), **R1** ("I felt compelled to behave as I would in the real world when deciding whether to cross the road in the virtual world"), and **R2** ("I felt compelled to avoid collisions with vehicles on the road."). In short, despite the low visual fidelity and graphic style of the simulation being recognized by participants as game-like, participants still largely felt that the simulation was consistent with the real world. More significantly, participants still treated the events and consequences in the VR experiments with seriousness relative to their own real-world experiences.

9.1.3 Situational Verisimilitude. Our results suggested that additional qualities of the VR experience were at work alongside and perhaps beyond visual fidelity in driving people's perception of consistency and consequence within the VRE. This was evidenced in the contrasting answers between **P11** and **P10** / **pR1** / **R2**. When asked about their thoughts on verisimilitude of the roadside that they were presented with, many participants cited that the vehicles and agent-pedestrians seemed realistic, despite their low-fidelity appearance. Here, we attribute that to what we term as, "situational verisimilitude", i.e., the appearance of contextual reality. This verisimilitude, we argue, comes from a combination of the user's ability to marshal their own senses and skills naturally in the VR, as well as their acceptance that the local actions of simulated pedestrians and vehicle drivers were in some way doing the same. In other words, users behaved realistically in the VR because they thought the phenomena that they encountered were running realistically.

Regarding vehicles, many participants felt that the ways vehicles in the simulation acted and were animated followed closely with how vehicles in the real world behave. Participants cited the varying velocities of cars as one realistic aspect, often quoting how vehicles in our city, for example, are unpredictable and that there seemed to be proper attention to this detail in how some cars occasionally moved faster than expected. One participant remarked that despite recognizing that the world was fake as per the visual fidelity of the environment, they were not so perturbed by it because of dynamic events happening in the environment that aligned with their expectations for how vehicles, ambient pedestrians, and traffic lights ought to work in the real world. For example, a vehicle's wheels animated to turn in response to the vehicle's velocity was a cue to this participant that the virtual vehicles matched the abstract notion of how cars ought to appear and move in the real world. A major complaint from participants that reduced the vehicles' realism was the lack of slowing-down behavior, as real-world cars in our city tend to slow down or engage in a sort of slow crawl maneuver to let waiting pedestrians cross because of the local red light turning rules, but no vehicles demonstrated that interaction in our VR. However, this did not detract people from treating the vehicles as any less realistic.

Agent-pedestrians received mixed responses from participants. Some cited that the agent-pedestrians moved realistically according to their expectations for how people in our city normally negotiate their movement at roadsides. Some participants cited that they treat both real-world and virtual pedestrians as obstacles that prevent them from observing road conditions and typically found themselves adjusting their position on the sidewalk to find better angles to look at the road. Two participants highlighted that the way agent-pedestrians rotated their heads to look at approaching vehicles fell in line with expectations, with one attributing the head-turning to a supposed "judgmental" reaction from the agent-pedestrians, thinking that they agents were looking at the participant with some level of disapproval of their attempt to cross the street before the crossing signal indicated "Go". Again, this is an interesting finding as it indicates the strength of rather simple gesturing behavior of our agents in producing a quite distinctly-recalled reaction from a user due to what could conceivably be regarded as social peer pressure and norm expectations. For another user-participant, this possibility was not a factor at all: they simply regarded agent-pedestrians' head-turning to them "swishing their hair". Other participants felt unconvinced about treating the agent-pedestrians as realistic due to their "awkward" animations while moving and their sometimes making crossing decisions that surpassed participants' thresholds for safety (i.e., the agents were too skilled at crossing to be regarded as authentic, despite our stochastic procedures for animating them). Fortunately, participants who remarked about this also noted that it was also how they treated pedestrians in the real world and that they typically also do not trust other pedestrians, meaning their perspective towards agent-pedestrians is similar to how they treat real-world pedestrians by simply ignoring them.

Audio was an additional layer of complexity that both elevated and reduced situational parity to the real world. Participants remarked that engine sounds coming from the vehicles added an additional metric by which participants could judge the relative positions and speeds of cars (i.e., by audio-localization). 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. However, the lack of broader environmental audio such as conversations between agent-pedestrians, construction sounds in the background, etc. was a noticeable omission to many participants who felt that the lack of ambient audio distracted them from the task at hand. This is possibly a unique feature of urban environments, where a cacophony of background noise is usually ever-present.

9.2 Validating Subjective Responses with Real-World Studies and Metrics

Verisimilitude (sense-based realism) is one aim of the study. Fidelity, i.e., exactness relative to real-world processes, is another aim. We consider the influence of both as design channels for constructing and deploying human-involved experiments in VR. For the VR experiments to be useful in informing domain science involving human subjects, we need them to be capable of supporting tests of theoretical and observational suppositions from the real world. In particular, for road crossing safety, we must expect that the VR experiments can reproduce processes, phenomena, scenarios, and observations that are authentic to real systems. To ensure that the perspectives of participants towards the exactness of the simulation dynamics are valid, empirical metrics were recorded as a means to validate whether people's behaviors matched those found in real-world studies. In other words, if the VR supports users' ability to reproduce known behaviors from the real world, we can regard it as having sufficient fidelity for experiments.

One of the key signals of variation in road crossing behavior (particularly safe and unsafe behavior) in the literature is sourced in demographic differences of crossers. In our VR, our findings suggest that participants' sex had a statistically significant effect on road-crossing behavior (specifically # of red-light violations and trial duration), which is to say that Females tend to be more cautious than their Male counterparts. This is identical to studies conducted in the real world. Statistical analysis of other factors such as Age Group and Prior Witness and/or Involvement in Pedestrian-Related Accidents are limited by a small sample population and the relative rarity of accidents to begin with. Nonetheless, the fact that trends do appear to follow existing knowledge gives credence to participants' subjective experiences within our VR simulation. We detail some of these findings below.

9.2.1 Differences Between Male and Female Pedestrians. Statistical analysis from our study indicates that the *Sex* of participants had a significant effect on **# of Red-Light Violations** and **# Trial Duration**. This falls in line with existing knowledge regarding different strategies employed by real-world pedestrians [Hamed 2001; Rosenbloom 2009], which observed Males performing more red-light violations than their Female counterparts. Studies conducted in the real world by Hiemstra et al. [Heimstra et al. 1969], Holland and Hill [Holland and Hill 2007], Moore [Moore 1953], and Yagil [Yagil 2000] have also observed differences in Male and Female behavior, specifically that Females display greater levels of caution when crossing at risky situations.

9.2.2 Effects of Age on Road-Crossing Behaviors. A surprising result from our data was that there was no statistical evidence for the effect of age on road-crossing behaviors in our simulation. This is in stark contrast with many (but not all) studies in the real world, which typically validate that younger pedestrians such as children and adolescents tend to demonstrate risky behaviors than adults in the real world [Hamed 2001; Ren et al. 2011; Rosenbloom 2009]. Our findings instead correlate with those of Mirzaei-Alavijeh et al. [Mirzaei-Alavijeh et al. 2019], whose participant pool also featured adults between the ages of 19 to 30 and whose analysis also did not demonstrate evidence for statistical significance on the effect of age towards road-crossing behavior.

9.2.3 Previous Experience with Accidents on Road-Crossing Behavior. Prior research [Hamed 2001] highlights that those who have experienced road crossing accidents tend to demonstrate more caution in their behavior at the roadside, especially as measured by longer waiting times prior to crossing. Our VR study showed this effect: we found that participants who had witnessed or been involved in pedestrian-related accidents tended to have fewer red-light violation attempts. Somewhat counterintuitively, our study found statistical significance in the effect of prior witness and/or involvement in accidents with the # of vehicle collisions. Those with prior experience collided with vehicles more than other groups. This can be potentially explained by the fact that vehicle collisions in the VRE were rare and sparse enough that occurrences of vehicle collisions are mostly chance occurrences.

9.3 The Connection Between Verisimilitude and Behavior

Subjective accounts from participants indicated that despite the low-fidelity appearance of our VR simulation (relatively low-resolution in polygon meshes and relatively low-resolution in texturing), our system presented high levels of verisimilitude, and that this design factor was empirically valid in inducing participants to engage in realistic behaviors in the VR. Broadly speaking, this level of verisimilitude was not achieved with agent-pedestrians (and some participants still treated the simulation like a video game, treating their ambient agents as non-player characters). Rather, the verisimilitude came from participants' marshalling of their own behavior relative to the *vehicles* in the simulation. In other words, users felt convinced that they ought to avoid being hit by cars and stated they felt compelled to employ real-world strategies and their real faculties to do so.

Our experiments were established to factor visual resolution, verisimilitude, and process fidelity and it is possible that other design channels that we did not account for are also at play. Nevertheless, the disparity between the low visual fidelity of our simulation's graphics and participants' strong inclinations to follow real-world strategies in our simulation is statistically valid in our findings. Explaining *why* is perhaps a broader topic. Here, we offer some suggestions to the reader. It is perhaps no question that a pedestrian's compulsions in performing road-crossing behaviors inside VR simulations rely inextricably on the design of those VREs as well as subjective interpretations of VREs from within pedestrians themselves. A number of (often necessarily subjective) qualia such as "immersion" and "presence" are commonly used in the lexicon of studies related to pedestrian simulators. Indeed, they are commonly invoked to reference experiential qualities of VR generally, under the umbrella concept of VR's ability to allow users to imagine "being there". However, our observations have shown that something beyond visual fidelity drives participants' feelings of presence and–importantly–also *engagement* of the virtual environment. Our analysis points to some evidence that the dynamic actions effected by agent-pedestrians and vehicles are a key factor in establishing embodiment between the user and the VR, critically by a sort of benchmarking by users of their expectations for the experiment being run in the VR setting. In short, we offer the argument that the local action models (in our case they are agent-pedestrian behavior trees and the IDM driver model for vehicles) are responsible for driving this embodiment. We expect that other allied local action models could advance users' sense of embodiment further, particularly via social agency, which would offer additional experimental levers for examining issues of peer effects, legitimacy, risk tolerance, crowding effects, and other observed phenomena from safety science. These, we argue, are all topics that are already achievable in VR through existing schemes for character animation [Oxley et al. 2005b].

9.3.1 "Plausibility Illusion". These observations fall in line with what Mel Slater described as the concept of "Plausibility Illusion" [Slater 2009], a subset of what is typically described as "Presence". Slater identified two subcategories of immersion that need to be addressed in the design of VREs: "Place Illusion" and "Plausibility Illusion". "Place Illusion", commonly known as the sense of "being there" that we just alluded to, involves the extent to which an observer feels that they are within a VRE despite knowing it is fake. Slater warns that Place Illusion typically breaks when an observer investigates the limits of the virtual environment and it behaves contrary to what is expected. However, the related phenomenon of "Plausibility Illusion" may alleviate concerns regarding breaks in Place Illusion. Plausibility Illusion centers on the feeling and impression that a user garners from the events as they unfold or are encountered in the VRE (primarily polled and cognized through their senses). In particular, the Plausibility Illusion works to convince the user (or their brain) that those events are actually happening, despite the user knowing that the event is taking place in VR. A typical example is a virtual asset such as a non-player character interacting with a user and the user then reacting in kind, despite knowing full well that the virtual agent is not real [Pan and Slater 2007].

Simeone et al. clarified this further by emphasizing that people will follow "adherent behavior", or behavior that is similar to what is expected in analogous real-world situations, if users are motivated to (1) follow routine behaviors born from life experiences and/or (2) avoid potential consequences, even if presence scores are low [Simeone et al. 2017]. Research in road-crossing actually indicates some of why this may be the case: safety in road-crossing, for example, exhibits strong peer influence among adolescents and also among adults [Pfeffer and Hunter 2013] . The first motivation implies that if VREs provide experiences that do not resemble real-life situations or follow expectations, then an observer's suspension of disbelief may be dismissed [Simeone et al. 2015]. Another implication is that the same visual aesthetics of a VRE may induce differences in how different observers perceive the same thing (in particular in how they may that perception to their skills and judgment), due to differences in sex, personality, learned behavior, and pre-existing expectations [Guadagno et al. 2007; Wieser et al. 2010]. Simeone et al. ultimately emphasized that the visual aesthetics of a VRE must be carefully maintained since difficulties in interpreting a virtual object's nature can increase the probability of confusion among observers. This is not to say that the graphics must necessarily realistic, but rather that graphical fidelity must make it clear *what* it is that observers are looking at (e.g., a person, a car, a road crossing) and not leave it up to interpretation of what a virtual object might be.

Slater and Simeone et al.'s observations may explain why, despite the knowledge that all elements of a VRE may be fake, people still react to them as if they are endowed with human characteristics, and why they can be persuaded (or entertained) into treating them as if they were realistic. For example, in other researchers' examination of VR experiments, users placed into virtual crowds have been enticed into avoiding collision with virtual agents [Koilias et al. 2020; Nelson et al. 2020] and into following changes in group behavior [Rio et al. 2018], and there is prior evidence from VR simulation to show that people avoid virtual vehicles despite knowing they are not really there and that no actual harm will come to the participant should they collide [Simpson et al. 2003b].

9.3.2 Implications of Plausibility Illusion in Future Traffic Flow Simulations. Slater and Simeone's notes on the topic may give designers an idea of the direction that simulators must take when designing experimental VR scenarios to study or even measure human behavior. The fidelity of graphics in a VRE is just one aspect of the experience and may only be required to be advanced should more complicated visual effects be the main subject of study. Perhaps equally important (beyond a minimum level of acceptable graphical quality), perhaps, is that dynamic events happening in the VRE adhere to established expectations of how real-world objects ought to behave, born from subjective, individual experiences of participants themselves. This requires extensive discussion with people on the ground–and with domain experts–to understand how real-world environments (built, social, physical, event-based) and their qualia affect individual factors that might drive that behavior, whether from people's perception of conditions from the context of the VR environment, or from the experiences that they bring to the experiments from different cultural, economic, and social backgrounds.

9.4 Design Recommendations Towards Higher Levels of Verisimilitude

Compiled below is an aggregated list of observations and recommendations from participants towards the goal of inducing greater levels of Plausibility Illusion and verisimilitude within observers of VR-Based pedestrian and traffic flow simulators.

9.4.1 Hardware Requirements.

- **Choice of hardware dictates comfort, physical stress, and place illusion**: Choose VR head-mounted displays (HMDs) that offer different levels of IPD (interpupillary distance) and are light to carry and/or distribute their weight evenly around the observer's head. HMDs that are too forward-heavy or do not offer customizability options restrict potential participant pools and may induce higher levels of physical stress. Heavy HMDs may also clue observers in that what they're seeing is not real and distract them from their tasks in the VRE.
- **Choose wireless options, if possible**: HMDs that offer wireless capabilities offer an extended level of freedom for observers. A tethered setup limits the traversable area and may distract participants by reminding them that they are not in the real world. A wireless setup also may reduce fears of breaking sensitive hardware.
- **Placement of base station sensors**: If the HMD of choice uses outside-in tracking through the placement of base stations (or lighthouses) around a traversable area, ensure that all base stations are oriented such that the HMD is always in line-of-sight with at least one base station. Improper calibration and/or placement of these sensors may create moments of lag in the simulation, which drastically reduces immersion, place illusion, and Plausibility Illusion.
- **GPU and CPU**: The choice of GPU and CPU is key to high performance and high frame rate in the simulation. However, these alone will not remove the simulation from lag or visual glitches. To reduce the chance of this happening while the simulation is running, ensure that the game engine the simulation is running on is allocated enough processing power first prior to any extraneous software such as video capture software.

9.4.2 Low Graphic Fidelity Options. Choices regarding the graphic fidelity of the system must be carefully selected to ensure that Place Illusion is maintained. The choice to go low-fidelity with a virtual environment may be preferred if hardware limitations exist, but certain factors must be accounted for to prevent Place and Plausibility Illusion from breaking.

- **Distractions in static elements**: The effect low-fidelity graphics have towards the verisimilitude of static environmental elements such as buildings, plants, and trees depends greatly on the amount of "abstraction" associated with that element in the real world. For example, trees can afford to be low-fidelity and simple due to how visually abstract they can be in appearance, whereas buildings are not afforded such abstraction. In this situation, the participant must be distracted from focusing on the appearance of these elements. This can be done through interactions and events that happen in relation to these elements (ex. doors opening/closing, smoke or noises coming from open windows, and people moving inside of buildings).
- **Little details in dynamic elements**: Similar to how abstractions of real-world objects may influence observers' perceptions of static objects, abstractions also affect perceptions of dynamic elements, though these abstractions will be more centered around how these dynamic elements move and behave. Small details that encourage those abstractions (ex. wheels moving on moving vehicles, lighting effects from cars' headlights or traffic signals in dark conditions, and pedestrians shuffling around while standing) will distract participants and give them an opportunity to embody real-world attributes in those dynamic objects, increasing Plausibility Illusion.
- **Avoid too low-poly meshes**: While low-fidelity graphics may be preferred, do not attempt to reduce mesh complexity in elements close to the observer to the point that observers can clearly identify edges or vertices in a mesh. Doing so will reduce immersion and Place illusion.
- **Go for higher graphics if nothing else**: If the problems above cannot be avoided, then the only remaining option is to upgrade the graphic fidelity of the virtual simulation. Be warned that if one element is improved, all elements must also be improved as well to avoid Place Illusion from breaking due to disparate levels of graphic fidelity in the environment. Furthermore, the more realistic an environment is made, the greater the risk of the uncanny valley effect.
- **Use optimizations where necessary**: optimizations such as occlusion culling will help to reduce the amount of stress on the system's GPU. Optimizing scripts and meshes is usually performed near the end of development cycles, but doing so will increment the performance of the simulation in small ways.

9.4.3 Dynamic Elements and Plausibility Illusion. The goal of VR-based simulations is to induce observers into performing as they would in the real world. This requires extensive focus on establishing Plausibility Illusion. This can be done by implementing events that are not induced by the observer's actions or presence.

- **Pedestrian behaviors**: If the VRE requires pedestrians to be nearby the observer, then it is crucial that they display a high-enough level of verisimilitude with attitudes from real-world participants to induce some level of Plausibility Illusion. This is highly context-dependent on location, time of day, and cultural norms. For example, pedestrians playing with phones, holding accessories such as coffee cups, listening to music, or talking with other pedestrians will instill high levels of verisimilitude in environments replicating heavily urbanized locations.
- **Ambience and sound**: Ambient noise will populate the background of the VRE and make observers feel more comfortable in the virtual environment, as long as ambient sounds are commonly heard in the real world the VRE is trying to mimic. Vehicle noises in the distance (ex. cars honking, tires skidding) and street noises (ex. pedestrians arguing, music playing, crosswalks beeping) will feel natural and improve Plausibility Illusion through higher levels of verisimilitude.

- **Animate interactions between vehicles, pedestrians, and the observer**: The observer needs to feel present within the environment to the extent that their actions have a tangible effect on the VRE's current state. Like with **pedestrian behaviors**, observers' actions must be able to incite a reaction out of other dynamic elements. Physics animations, other pedestrians reacting to observer movements, and vehicles reacting to pedestrians close to or on the road will increase feelings of verisimilitude, thereby improving Plausibility Illusion.
- **Add consequences**: A big part of verisimilitude and Plausibility Illusion is the threat of consequences. Observers in VR simulations must be able to feel that consequences carry over in some metaphorical way to the VR condition. A "Lose" state or condition, for example, when an observer is struck with a vehicle or performs a dangerous action may induce feelings of frustration and stress, but these will bring the simulation one step closer to a higher level of verisimilitude and consequently a higher level of Plausibility Illusion.

10 LIMITATIONS AND FUTURE WORK

There were several limitations to this study that could be overcome in future work. First, we relied on a participant sample that was relatively modest. This was enough to elicit statistical validity in the multivariate statistics that we used for empirical insight, but as we discussed in a few instances it introduces problems in explanation, when for example the behavior of a few individual participants cause possible shifts in results. A second issue centers around difficulty in isolating the influence of the VR simulation within some of the post-study questionnaire inquiries, especially those around Task Load. In this case, our questionnaire and interview instruments may have been limited in their ability to reveal preferences in respondents. This is an unfortunate function of the huge variety of potential motivating factors that govern individual's explanations of their behavior, even over a modest sample of participants. For example, participants may already naturally find it mentally demanding or physically demanding to pay attention to cars in the real world, and the lack of any metric to reveal that factor may limit analysis for its presence in our VR experiments. This could have been avoided by having participants perform a close-to-equivalent task in the real world, having them navigate a similarly-sized *actual* intersection or road and have them fill out the same Presence-Realism-Task Load questionnaire so that we could map real and virtual findings. Other researchers in walking studies [Latham 2008], for example, have reported some success with asking participants to narrate their decision-making as a diary while they engage in the experiment; this is difficult for our domain of road-crossing, where we rely on users paying attention to events in the simulation with hyper-awareness, and eschew distractions that would be cause by asking them to self-report what they are thinking.

Finally, although we have touted the ability of our system to evoke naturally-realistic and faithful behavior from participants in the absence of high-resolution graphics, it is nonetheless most likely that enhanced visual representations would contribute significantly to users' experiences in the simulations and would enhance their sense of presence and the plausibility of the VR, with the result that perhaps even more real behaviors could be produced in VR-based experiments. Here, we can mention several options that graphics would assist with, including the lighting effects mentioned by our participants, but also issues of reflection from puddles on the road and on store windows that could factor into people's early detection of oncoming traffic, rustling of trash on curbsides as an indicator of vehicle speed, and animation of headlights onto the road surface as a precursor of approaching vehicles. We regard this aspect as a design channel that is already well-traversed in the computer graphics community and well within reach, and our point in this paper is to highlight what can be done by advancing capabilities on other "adjacent" channels of verisimilitude and fidelity. Hints that other factors could and should also be incorporated along with sophistication and nuance in graphics such as rendering are apparent in the reports from our users: e.g., the lack of ambient noises in the background, the lack of incorporating weather, and limitation in lighting effects was raised by participants as a barrier to what could term the plausiblity illusion. No doubt, this "drags" on the success of verisimilitude and fidelity in ways that we are just not measuring. Again, we note that these dimensions of VR are already well-treated in the literature and in the state of the art and would be straightforward to incorporate in platforms such as *Unity*. We also offer that our study is capable of highlighting which of these extraneous factors are causing concern among participants, with the implication that they could be "turned on" from pre-existing simulation capabilities if and when needed for an experiment.

11 CONCLUSIONS

This study has tested the ability of low-level action models to endow dynamic agents in VR with *realistic-seeming* and *realistic-behaving* actions. Our results show that an approach that embraces this task with dedicated location action models can be useful in two critical ways: by emphasizing (1) verisimilitude, alongside (2) fidelity in VR. We contend that this can ultimately lead to the use of VR in diagnostically useful and theoretically valuable experimental scenarios for real domain science. We have demonstrated this with regard to safety science for road-crossing behavior, where VR is perhaps an essential tool for experimenting with human factors that are otherwise far beyond experimentation in tangible and physical form. Our experiments demonstrated that low-level action models for simulated pedestrians and vehicles in VR can elicit natural behavior from user-participants, and also that they can produce experimental scenarios that have application value relative to theory. This, we consider, shows that verisimilitude and behavioral fidelity can help to close the loop between VR and real-world phenomena, providing valuable experimental media in between. Not all dynamic elements in our system were found to properly capture the same level of verisimilitude. Indeed, users reactions on both counts were different across vehicles, agent-pedestrians, and traffic signals. This opens the broader question of where, specifically, high-fidelity models should be developed to underpin VR assets, and what aspects of verismilitude might be important considerations for designers of VR media. This is a topic for future research, which would benefit from analysis of other domain experiments, beyond road-crossing.

Quite possibly, it is a topic that could fold under existing efforts to develop Simulation-Based Engineering and Science [Oden et al. 2006], or computational social science [Torrens 2010]. Nevertheless, we consider that we have demonstrated evidence that users' feelings of presence and immersion extend beyond the graphical fidelity of VREs, which provides new (opportunistic) channels for the development of graphics and animation for VR assets that can more realistically capture realistic and/or theoretically plausible patterns in real-world scenarios.

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