Monkey See, Monkey Break? Study of Rule-Breaking Imitation in Virtual Crowds

Kexiang Huang, Tairan Yin, Jose Luis Ponton, Ruida Tang, Reiya Itatani, Gangyi Ding, Oscar Argudo, and Nuria Pelechano

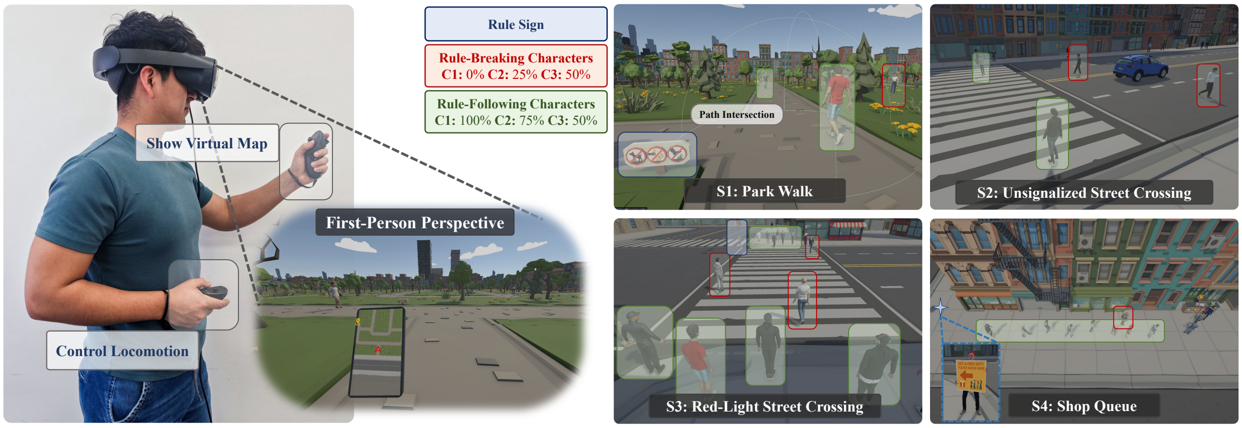

Fig. 1: The 4 scenarios of our immersive virtual environment for the present experiment, populated with rule-followers and rule-breaking virtual characters (detailed in Sec 3.3). **Top-left** (S1): Park walk. **Top-right** (S2): Unsignalized street crossing. **Bottom-left** (S3): Signalized street crossing. **Bottom-right** (S4): Shop queue.

Abstract— Rule-breaking behaviors, such as jaywalking or skipping queues, are common in crowds but difficult to study in real-world settings due to limited control and observability. Virtual reality (VR) provides a controlled alternative, but its validity depends on whether VR elicits realistic rule-breaking behavior. We conducted a VR study with 65 participants navigating a virtual city with four scenarios differing in social norms: walking on grass, crossing outside a crosswalk, jaywalking at a red light, and skipping a line. In each scenario, the proportion of rule-breaking virtual characters was manipulated (0%, 25%, 50%). Participants' movements and gaze were recorded to assess behavior and attention. Results showed higher rule-breaking as the number of violators increased, except in the low-stakes crossing scenario. Rule-breakers attended more to violating characters, whereas rule-followers focused on compliant ones. Participants cited efficiency, safety, and social norms as key factors guiding their decisions. Overall, VR reproduced natural patterns of social compliance and noncompliance, supporting its use for studying rule-breaking and applications in crowd simulation, urban design, safety training, and immersive media.

Index Terms—Social imitation, rule breaking, virtual reality, crowd simulation.

1 Introduction

Rule-breaking (RB) is pervasive in everyday life, such as walking on grass or jaywalking. Prior work has identified social contagion effects, whereby an increasing number of violators raises the likelihood that others will follow [13], potentially leading to snowball effects that disrupt public order, especially in high-stakes contexts like pedestrian crossings where safety risks increase [43]. However, it remains unclear whether established social influence mechanisms (e.g., conformity [4]) fully transfer to RB contexts and what the precise dynamics are. While field studies provide valuable insights, they are limited to observation [61], constrained by ethical and safety concerns, and offer limited access to critical data such as eye-gaze and local movement patterns.

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Recent reviews call for controlled, ethically sound VR studies that systematically manipulate social exposure while capturing behavioral and perceptual data to investigate the mechanisms underlying collective rule-breaking [43]. In VR we can capture detailed behavioral data, such as participant trajectories, and analyze the relationships among distances, detours, timing, and decisions. In addition, gaze tracking provides an objective measure of visual attention, which has been shown to be closely linked to decision intention and risk assessment [23]. Prior VR studies of high-stakes scenarios, such as fire evacuations [60], have shown that participants' behavior closely mirrors real-world responses. However, it is unclear if this holds for low-stakes rule-breaking, where reduced real-world consequences and residual perceptual artifacts inherent in VR may lead participants to down-weight social cues, potentially weakening social influence. In an immersive virtual environment, when users observe virtual agents breaking a rule, do they imitate the rule-breaking behavior? Does this imitation increase as more virtual characters break the rule, and is there a point at which it stops increasing? Will we observe a similar pattern across different virtual scenarios?

To address these questions, we designed a between-subjects VR experiment with four representative scenarios of varying normative stakes: walking on park grass, crossing outside a crosswalk, jaywalking at a red light, and skipping a queue (see Figure 1). To enable controlled exposure of social influence, we manipulated the proportion of violating virtual agents (0%, 25%, 50%) in each case. Local trajectories and gaze data were recorded to derive exposure-sensitive metrics that capture how participants perceived and evaluated their surroundings before deciding whether to follow or break rules. Our results show that the presence of rule-breaking characters increases participants' rule-breaking extent, and that scene-invariant individual consistency strengthens as the proportion rises.

Our contribution in this work are:

1. We studied the ecological validity of rule breaking behavior with four representative scenarios of social rules.

2. We studied the coupling between observation and gaze with rule breaking behavior.

3. We provide insights to inform the design of more socially believable and immersive virtual crowds.

After discussing related work in Sec. 2, we introduce the system design in Sec. 3, and describe our experiments in Sec. 4. Sec. 5 present the analysis methodology, followed by results in Sec. 6. We discuss the main findings in Sec. 7, limitations and insights in Sec. 8, and conclude in Sec. 9.

2 Related Work

2.1 Social Influence and Norm Violation

During individual-crowd interactions, the behavior of a crowd can influence not only what the individual attends to and perceives, but also how the individual acts [43], even when the crowd's behaviors are incorrect [3, 4, 21]. Such an effect of social influence leads to a wide range of rule-breaking or norm-violation behavior from relatively harmless infringements (e.g., jaywalking [33, 46, 61], queue jumping [1, 22], and off-trial walking [31]) to risky and dangerous acts (e.g., looting [55], violence [11]). In these phenomena, individuals tend to join spreading disorder [38, 68], often imitating the behavior of those around them. Research on collective rule-breaking emphasizes social conformity [3, 4]. When exposed to non-compliant groups, individuals' perceptions shift between descriptive ("*what most people do*") and injunctive ("*what people approve of*") norms [9], involving attention to non-compliant groups [29], imitation of others' actions [14], and adjustments in risk or ethical evaluation [8, 72].

Social influence can be contagious, resulting in the transfer of rule-breaking behaviors and the cascade effect in nonconformity. Such "*drawing power of crowds*" [50] has been an interesting research topic [9, 32, 44]. Previous studies have demonstrated that "*first movers*" significantly increase the likelihood that others follow—group size, status cues (e.g., attire), and impatience all raise violation rates [33, 46, 61]. In addition, the number of noncompliant individuals is crucial to the force of social influence [44]. Multiple agents performing the same behavior elicit strong motor activity [15, 16], eliciting a reflexive tendency to follow their behavior [43]. Thus, larger groups induce stronger imitative responses [13], facilitating both active rule-breaking and passive bystander (i.e., non-action) behaviors [16]. Multiple efforts have been made to mathematically model collective rule-breaking behaviors [12,18,20,24,36,56]. To date, most studies have focused on specific cases. Among these, jaywalking is one of the most studied cases due to its relatively easy data collection from field observation [62]. The contagion of jaywalking behavior depends on individual evaluation of potential danger and the number of rule-breaking pedestrians [23]. Du et al. [23] demonstrated that, in high-risk situations, pedestrians paid more attention to vehicle hazard cues before making jaywalking decisions. Khuzam et al. [39] further revealed that rule-breaking pedestrians present erratic and difficult-to-predict movement with sudden speed changes and a higher speed than rule-follower pedestrians.

It is important to note that case studies of rule-breaking are often limited by technical and ethical challenges in real-world or lab settings, making it difficult to capture high-quality data on what each pedestrian sees and decides in crowded scenes [43]. Nevertheless, most research relied on manual sampling to categorize pedestrian movements observed from video cameras [62]. The lack of automatic data capture and processing approaches restricts further research.

2.2 Individual-Crowd Interaction in VR

VR has emerged as a powerful tool for studying complex human behaviors in the virtual world, ranging from risk-taking and rule-breaking [19, 51] to reactions to crowd behaviors [26, 34]. This kind of experiment requires immersing a user into the virtual environment and interacting with virtual characters driven by either prerecorded animation [69, 70] or real-time simulation [54, 71]. Compared to empirical studies in the real world, VR provides a series of benefits, including high controllability and reproducibility, as well as a low ethical risk of danger and physical damage. On the other hand, VR introduces a number of perceptual and behavioral biases to users, such as affecting depth perception [2, 48, 59, 67], social distance with virtual characters [5, 7, 28, 47], and gaze patterns [6]. In addition, the level of immersion, highly influenced by the sense of embodiment and social presence, is critical to ensuring natural user behaviors during the VR experiments [63]. However, despite quantitative differences, these studies generally agree that user behavior in VR is qualitatively similar to that in the real world [58, 69], supporting the use of VR to study crowd influences on individual behavior.

Multiple VR-based studies have discovered how virtual crowds can influence users' behavior. Some studies examined users' locomotion and affirmed that users adjust their behavior to match the velocity and density of their surrounding crowd [42, 54, 65]. Others addressed the social influence of virtual characters on the user, typically the effects of herd [53] and bystander [64]. A primary research focus is evacuation behavior under emergency situations [40, 41]. Moussaïd et al. [53] investigated path decision making during evacuation under high-stress. In contrast, Rios et al. [60] and Kinateder et al. [41] demonstrated that individual willingness to evacuate is respectively influenced by virtual characters' positive and negative responses to the simulated emergency. Slater et al. [64] investigated the phenomenon of bystanders using VR and demonstrated that people are more willing to help strangers when they are part of a group than when they are alone. In summary, existing studies show that VR is a validated platform for observing user behaviors that closely resemble real-life situations, providing valuable insights for crowd research.

2.3 Positioning

The present study bridges real-world social influence and VR research, examining everyday imitation behaviors in crowds. Unlike prior VR studies focused on emergencies, we investigate routine "*monkey see, monkey do*" actions in public spaces, such as street crossings, off-trial grass stepping, and queue jumping. This study serves as an ecological validation of VR for studying social decision-making in everyday situations and to propose a framework for collecting human decision-making data that can inform more plausible crowd simulation models in VR.

3 System Design

3.1 User Navigation

Users interacted with the environment using a head-mounted display (HMD) and two hand-held controllers. Locomotion was controlled via the joystick on the right-hand controller: participants could move in any direction by pushing the joystick, with the forward direction always aligned with the controller's orientation in the virtual environment. The navigation speed was mapped to the joystick's deflection amplitude and capped at a maximum of 2 m/s, allowing participants to dynamically adjust their walking pace while maintaining fine-grained control over their trajectory. For orientation and navigation support, a virtual smartphone was attached to the left-hand controller, displaying a dynamically updated map with the user's position and the next navigation target. To avoid introducing additional factors that could bias movement decisions, no self-avatar was rendered for the users [52]. Figure 1 illustrates this interaction setup.

3.2 Virtual Characters

Character Definition. We define two types of virtual characters based on their compliance with real-world navigation rules. **Rule-Following Characters (RFC)** navigate according to traffic rules and social conventions. **Rule-Breaking Characters (RBC)**, in contrast, neglect these rules and conventions, preferring shorter paths to accomplish their tasks more quickly.

Steering Strategy. The movement of virtual characters in all scenarios was controlled using a social force–based crowd simulation model [35]. To improve natural collision avoidance, we extended the classical model by incorporating two additional terms: (1) a short-range tangential friction force to model close-contact interactions, and (2) a long-range lateral perception force to simulate anticipation and early avoidance. Each virtual agent was represented as a circular disk with a radius of 0.5 m. Agent behavior was governed by navigation points (NP) that were defined according to the specific context of each of the four scenarios.

The steering strategy also took the user's information into consideration as a dynamic neighbor. This means virtual agents actively avoided collisions with the user by applying the same steering rules as for other agents. We assigned virtual characters' preferred velocity v_{pref} depending on their behavior. For **RFC**, v_{pref} was sampled from a uniform distribution in the range $[0.8, 1.6]$ m/s. For **RBC**, v_{pref} was increased, sampled from the range $[1.2, 2.0]$ m/s, to reflect more assertive and goal-oriented movements [30].

Animation. The movements of all virtual agents controlled by the social force model were animated using a Motion Matching approach [57]. Motion Matching synthesizes responsive and realistic character animations by using features such as foot positions and velocities, hip velocity, and future trajectory directions as query vectors to search within a motion database for the best-matching sequence. Compared to conventional walking cycles, Motion Matching provides smoother transitions and reduces artifacts such as foot sliding, resulting in more natural locomotion for agents in the environment, thereby increasing realism in VR.

Appearance. To increase visual diversity in the crowd, we selected a total of 50 unique character models, consisting of 29 male and 21 female avatars. Among these, 21 models were sourced from Adobe Mixamo and 29 models from the Microsoft Rocketbox avatar library. We ensured that each scenario contained a balanced mix of male and female characters and avoided duplication of the same model within a single scene. To reduce the risk of uncanny valley effects and maintain consistency with the overall environment, we adopted a stylized, semi-cartoonish visual appearance for the virtual crowd. This choice aligns with prior findings indicating that both photorealistic and non-photorealistic environments can effectively elicit a strong sense of presence [49].

3.3 Scenarios

To maintain coherence and immersion throughout the experiment, we designed a continuous task that naturally guided participants across all experimental scenarios. The task narrative required participants to (1) exit the park area, (2) collect a virtual coupon at a designated location, and (3) redeem the coupon at a shop to obtain a gift. This goal-oriented task provided natural motivation, allowing users to experience the scenarios as part of a single, larger journey, while simultaneously diverting their attention from the study's actual research focus. Building upon this continuous task, the virtual city was populated with four scenarios (Figure 2), each designed to illustrate different situations in which rule-breaking behavior varies in both severity and potential danger. For example, walking on grass may be considered harmless and perceived as a minor or *soft* rule, whereas crossing traffic at a red light constitutes a dangerous act and is regarded as a more serious violation.

S1: Park Walk. This scenario replicates a real-life situation in which pedestrians walking in a public park may decide to step on the grass, even when it is prohibited. We designed a rectangular park of size $150\,\text{m} \times 90\,\text{m}$ in the virtual environment, containing multiple walking

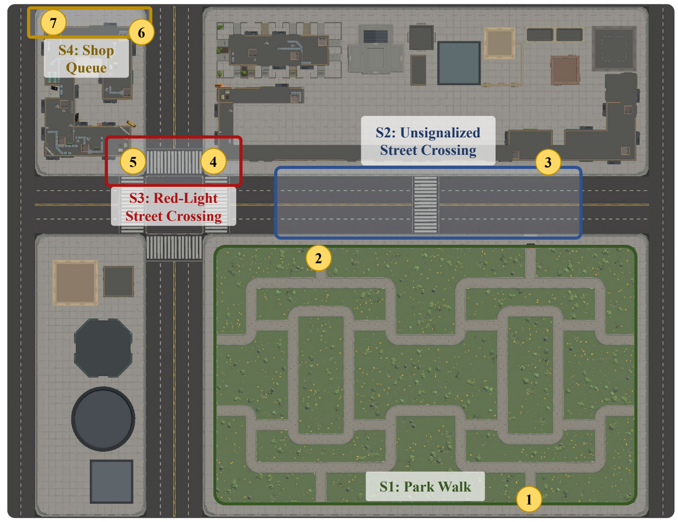

Fig. 2: Our virtual city included four rule-breaking scenarios. Yellow numbered markers indicate the Navigation Points (**NP**s) that sequentially guide participants through the environment.

paths surrounded by grass. Several signs were placed next to the paths, displaying icons such as "*no stepping on grass*", "*no picking flowers*", and "*no pets allowed*". Among these, only the "*no stepping on grass*" rule is relevant to our study (see Figure 1): the others were included to mimic real-world signs and to prevent participants from easily identifying the experimental intention behind this scenario. The park is populated with 50 virtual characters. All the **RFC**s follow the designated walking paths inside and around the park. At each intersection, a character randomly selects its subsequent route, ensuring variability in trajectories. By contrast, all **RBC**s directly walk from one randomly chosen point on a path to another, cutting across the grass. This scenario starts at NP1 and ends at NP2 (Figure 2).

S2: Unsignalized Street Crossing. This scenario is situated on a street measuring $90\,\text{m} \times 30\,\text{m}$. The participant enters the scene at NP2 and exits at NP3 (Figure 2). A single zebra crossing is placed in the center of the street, connecting both sidewalks. To enhance realism, multiple vehicles circulate along the street at a constant $10\,m/s$, yielding to pedestrians: when a pedestrian enters a $5\,\text{m} \times 8\,\text{m}$ detection zone in front of the vehicle, it decelerates at $-20\ m/s^2$ to a stop; once the zone is clear, it accelerates at $10\ m/s^2$ to regain cruising speed. Virtual characters move along both sidewalks and randomly decide to cross the street. All the **RFC**s walk toward the zebra crossing and complete the crossing using the designated path. **RBC**s randomly select a target position on the opposite sidewalk and walk directly toward it, disregarding the zebra crossing.

S3: Red-Light Street Crossing. This scenario occurs at a signalized intersection with zebra crossings. At the beginning, the traffic light is red. A total of 16 virtual characters wait on both sides of the crossing (NP4 and NP5 in Figure 2), performing idle animations from Mixamo. A detection zone is placed 12 m before the crossing, and the scenario is triggered when the participant enters this zone. At that moment, four vehicles pass through the intersection (two traveling north–south and two south–north), providing a strong visual cue that the traffic light is red. After these vehicles leave, no further traffic appears, and the street remains empty. The red signal lasts for 60 seconds before switching to green. **RFC**s wait during the red phase while playing idle animations. When the signal turns green, they cross using standard motion-matching animations. **RBC**s exhibit red-light violations: one initiates a red-light violation after the vehicles have cleared the crossing; nearby **RBC**s observe, hesitate briefly, and then also cross during the red phase.

To better capture perceptual cues and hesitation in jaywalking, we animated rule-breaking characters (RBCs) using the One-Man-Crowd

(OMC) [69] paradigm with Xsens motion capture. A single experimenter iteratively embodied and role-played each character while being motion-captured. When embodying the first character, the actor naturally looked left and right before deciding to cross. When embodying the remaining characters, the actor observed the previously captured animations and decided whether to imitate the violation, thereby reproducing realistic hesitation and decision-making processes. Characters transitioned from OMC animations to social force control with motion matching, so that OMC was applied near the crossing to enhance realism while the social force model governed subsequent local movement. The OMC paradigm allowed us to capture highly detailed animations that responded naturally to the situations rather than relying on simple walking cycles with a limited set of standard idle behaviors.

S4: Shop Queue. This scenario takes place in front of a gift shop, where 12 virtual characters are waiting in line to receive a free gift. At the end of the queue, a character holds a sign reading "*Please queue here*" (see Figure 1) to informally notify the participants that a queue is to be respected before retrieving the gift. All **RFC**s wait in the queue and move forward in turn as the first-in-line character receives the gift and leaves. In contrast, the **RBC**s approach the shop from a distance, disregarding the queue and stepping directly to the staff to claim their gift before leaving.

4 Experiment

In this section, we present the experiment designed to assess whether and how the presence and proportion of rule-breaking agents would influence participants' decisions to follow or break rules in different scenarios. To this end, we established three conditions representing different proportions of **RBC**s: **C1** (0%), **C2** (25%), and **C3** (50%). The experiment followed a between-subjects design, where each participant was exposed to only one of the three conditions. This design choice was critical to prevent participants from becoming aware of the manipulation through repeated exposure, thereby reducing learning effects, fatigue, and bias. Furthermore, it ensured a more natural and uninterrupted experience within the virtual environment while also keeping the overall experiment duration within practical limits.

Building on cognitive mechanisms [43] of collective rule-breaking and the expectation that rule-breaking decisions are shaped by the prevalence of other rule-breakers and low-level perception or evaluation of social cues, we formulated the following hypotheses:

H1. Participants' rule-breaking behaviors will be influenced by the behaviors of the virtual characters.

H2. Participants will exhibit consistent tendencies in their rule-breaking behaviors across the different scenarios.

H3. Participants' rule-breaking behaviors are related to low-level individual behavior (e.g., visual attention).

4.1 Apparatus

The VR application was developed in Unity 6000.0.39f1 and executed on a high-performance PC (Intel Core i9-12900HK, NVIDIA RTX 3080 Ti, 64 GB RAM). Participants experienced the virtual environment through a Meta Quest Pro head-mounted display (HMD) connected to the PC via Meta Quest Link. The headset provides a resolution of 1800×1920 pixels per eye, a refresh rate of 90 Hz, a field of view of 106°, and integrated eye-tracking capabilities for gaze-aware recording. OMC motion data for S3 was captured using the Xsens Awinda system.

4.2 Participants

A total of 69 participants ($M_{age} = 26.99$, $SD = 5.7$) took part in the study. The sample included 38 males (55.07%) and 31 females (44.93%). Participants were randomly assigned to one of three experimental conditions: **C1** (24 participants), **C2** (22 participants), and **C3** (23 participants). Due to data recording issues and motion sickness, data from four participants were discarded, leaving 65 valid datasets for analysis. A priori power analysis for a between-subjects design indicated that a sample of this size achieves adequate power ($> .80$, large effect).

Participants were recruited through an open online questionnaire and were primarily students and faculty members from the university. 30 participants reported high gaming experience, 24 medium, 13 low, and 2 no experience. 17 participants reported high VR experience, 21 medium, 23 low, and 8 no experience.

4.3 Experimental Design

Upon arrival, participants read and signed an informed consent form, during which the experimental task was explained. They were then instructed to put on the Meta Quest Pro headset and hold the two controllers. Each participant was assigned a unique random ID. In the virtual environment, participants first completed a short training scenario designed to familiarize them with the VR devices and navigation method. They were then immersed in a low-poly style virtual city and instructed to navigate to a designated point (identical for all participants). To ensure minimal motion sickness, the experimenter reminded participants to naturally hold the right-hand controller in front of their body while moving, so that their physical body orientation corresponded to the virtual movement direction.

After completing the training task, participants were transported to the experimental area of the virtual city, starting at the south entrance of a park (NP1 in Figure 2). The experiment then unfolded as a continuous task in which participants were instructed to go through four scenarios described in Sec. 3.3. Participants were free to decide how to accomplish each navigation step (e.g., which route to take) as well as whether to respect or violate social conventions. In this context, rule-breaking behaviors corresponded to stepping on the grass (S1), crossing the street outside the zebra line (S2), jaywalking during a red light (S3), or skipping the queue (S4).

During the experiment, we recorded participants' head position and orientation, left-hand position and orientation, and gaze direction at a fixed frequency of 50 Hz. All random processes (e.g., virtual character appearance, walking speeds, and navigation targets, as well as vehicle initialization) within the application were seeded using each participant's ID, ensuring that the experiment could be replayed afterwards for analysis purposes.

Upon completing the final task and receiving the virtual gift, the VR session ended. Participants were then asked to remove the headset and answer an open-ended questionnaire. They were invited to reflect on whether they had deliberately broken certain rules, to explain their reasons, and to provide subjective ratings of their overall experience. All procedures received approval from the Ethics Committee of the Universitat Politècnica de Catalunya (UPC),

5 Analysis

In this section, we present the analysis of the collected data to investigate how participants responded to the presence of virtual rule-breaking agents. The analysis combines objective behavioral measures with subjective self-reports, enabling us to capture the observable actions of the participants in the virtual environment and their perceptions of the overall experience.

5.1 Extent of Rule-Breaking Behavior

To capture the extent of rule-breaking behavior, we define scenario-specific metrics. Instead of using a binary indicator, the extent of rule-breaking was quantified based on spatial or temporal deviations from the expected rule-following behavior.

E_{S1}: Park Walk. In the park scenario, rule-following participants remained on the designated walking paths. For each participant i, we define the instantaneous rule-breaking extent at time t as the lateral deviation from the edge of the nearest path $d^i_{S1}(t)$. To compute the overall rule-breaking extent for the entire scenario, we normalized both the deviation and the duration of the trajectory to the unit interval. The normalized instantaneous extent is given by $e^i_{S1}(t) = \frac{d^i_{S1}(t)}{d_{\max}}$, where $d_{\max} = 10\text{m}$ denotes the maximum possible deviation from the path boundary in the scene. With $t \in [0,1]$ denoting normalized time, the total rule-breaking extent is then expressed as $E^i_{S1} = \int_0^1 e^i_{S1}(t)dt$.

E_{S2}: Unsignalized Street Crossing. In this scenario, rule-following meant staying within the zebra crossing while crossing the street. For participant i, we defined $d^i_{S2}(t)$ as the shortest lateral distance to the zebra crossing boundary whenever their position fell outside it; otherwise, $d^i_{S2}(t) = 0$. To evaluate the overall rule-breaking magnitude, we again normalized distance and trajectory duration. The normalized extent is expressed as $e^i_{S2}(t) = \frac{d^i_2(t)}{d_{\max}}$, with $d_{\max} = 10$m as the upper bound. The integrated extent E^i_{S2} is computed in the same manner as E^i_{S1}.

E_{S3}: Red-Light Street Crossing. In this scenario, compliance required participants to remain within the designated waiting zone during the red light, and begin crossing when it turned green. For participant i, the normalized rule-breaking extent was defined as the proportion of the red-light duration during which the participant was not waiting in the compliant area: $E^i_{S3} = \frac{\max\left(T_{\text{red}} - T^i_{\text{wait}}, 0\right)}{T_{\text{red}}}$, where $T_{\text{red}} = 60$s is the red-light duration (beginning as the participant approached the crossing), and T^i_{wait} is the time spent in the waiting zone. A positive value indicates that the participant crossed during the red light (i.e., jaywalking).

E_{S4}: Shop Queue. In this scenario, compliance required participants to remain in the queue until reaching the counter. For participant i, the normalized rule-breaking extent was defined as the proportion of time advantage gained relative to the last virtual agent in the queue: $E^i_{S4} = \frac{\max\left(T_{\text{last}} - T^i_{\text{gift}}, 0\right)}{T_{\text{last}} - T_{\text{init}}}$, where T^i_{gift} is the time when participant i received the gift, T_{last} is the time when the last **RFC** received theirs, and T_{init} is the initial time when the participant arrives to NP6 (Figure 2). Larger values indicate that the participant obtained the gift earlier than expected, i.e., by cutting the queue.

5.2 Trajectory Analysis

To better understand how participants moved through the virtual city while performing the task, and to enable a direct comparison of navigation patterns across the three experimental conditions, we analyzed participants' trajectories together with their associated rule-breaking extent. This allowed us to examine how compliant and rule-breaking behaviors manifested in different parts of the task and to identify systematic differences in movement strategies across scenarios. In the park (S1) and unsignalized crossing (S2) scenarios, rule-breaking was directly reflected in spatial deviations from compliant routes. We therefore evaluated the extent of rule-breaking along participants' trajectories. In contrast, in the red-light crossing (S3) and shop queue (S4) scenarios, rule-breaking primarily influenced task efficiency rather than path shape. Accordingly, we differentiated participants' overall trajectories based on their rule-breaking extent, which enabled us to assess how trajectories were related to differences in task completion time.

5.3 Visual Attention Patterns

To investigate the role of individual-level perception in participants' decision-making, we analyzed their visual attention during the experiment. Eye-gaze orientation data were continuously recorded from the HMD and later replayed together with participants' trajectories in each of the four scenarios. During this replay, gaze targets were classified into predefined categories (see Table 1). Any gaze falling outside these categories, such as background elements of the environment, was labeled as *None*. Gaze detection was performed using a cone-casting method. Specifically, from the participant's eye position, a cone with a 5° aperture and a maximum length of 50m was cast along the gaze direction. All objects intersecting the cone were identified, and their depth, lateral offset, and angular deviation relative to the gaze direction were computed. The closest object along the gaze vector was recorded as the current attention target.

To analyze the relationship between visual attention and participants' rule-breaking choices, we calculated the proportion of time participants spent gazing at specific object categories relative to the total duration of each scenario. We then compared these gaze patterns across conditions (C1-C3), scenarios (S1-S4) and between participants who either followed or broke the rules to explore associations between visual attention and actions.

Table 1: Categories of gaze targets and their definitions.

Label	Definition
RBC	Rule-Breaking Characters.
RFC	Rule-Following Characters.
Sign	Prohibition or instruction signs in the scene(e.g., *park sign*, *traffic light*).
Phone	The virtual phone attached to the left controller.
Vehicle	Cars moving in the environment.
Target	The current navigation target in the scene.

5.4 Post-Experimental Questionnaire

5.4.1 Perception and Experience

To evaluate participants' subjective experiences, we administered a Likert scale questionnaire (Table 2) focusing on two dimensions:
Perception of risk and social pressure: Assessing participants' judgments of rule-breaking consequences and the degree to which they felt influenced by the surrounding virtual crowd.
Experience evaluation: Focusing on the perceived naturalness of the virtual agents' behavior and the overall sense of immersion and engagement during the VR task.

Table 2: Questionnaire content. Items were rated on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree).

Perception of Risk & Social Pressure	
Q1	I felt that breaking the rule could lead to negative consequences.
Q2	I felt pressured to follow the behavior of the crowd.
Q3	I consciously evaluated the risks before making a decision.
Q4	I was more likely to break rules when more agents were doing it.
Q5	I felt safer breaking a rule when I saw others doing it first.
Experience Evaluation	
Q6	The behavior of the virtual agents seemed natural and human-like.
Q7	I felt immersed and engaged during the VR experience.

5.4.2 Reported Reasons

Beyond the quantitative ratings, the questionnaire included open-ended questions that asked participants to explain their decisions in each of the four scenarios, particularly whether and why they chose to break or comply with the rule. We analyzed subjective responses using an open coding approach, allowing up to three labels per answer. Two experimenters independently coded each scenario, with a large language model (OpenAI GPT-5) serving as a third labeler. The experimenters then reviewed all labels and reached a consensus on the final coding for each response.

6 Results

In this section, we report an overview of the results following the analyses in Sec. 5, focusing on differences in participants' behavior, perception, and evaluation across scenarios (S1–S4) and experimental conditions (C1–C3). For an in-depth discussion and interpretation of these findings, please refer to Sec. 7.

6.1 Extent of Rule-Breaking Behavior

We first examined the extent of rule-breaking across all conditions in the four scenarios, using the metrics E_{S1}–E_{S4} as defined in Sec. 5.1. Figure 3 illustrates the distributions across conditions.

Before conducting comparisons, we tested data normality using the Shapiro–Wilk test, which indicated frequent violations of normality. Consequently, we applied non-parametric methods. Table 3 summarizes

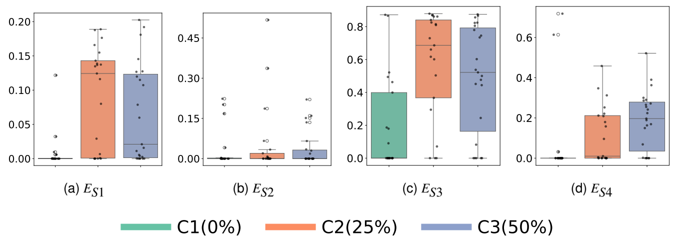

Fig. 3: Distributions of rule-breaking extent across conditions (C1-C3) in the four scenarios (S1-S4).

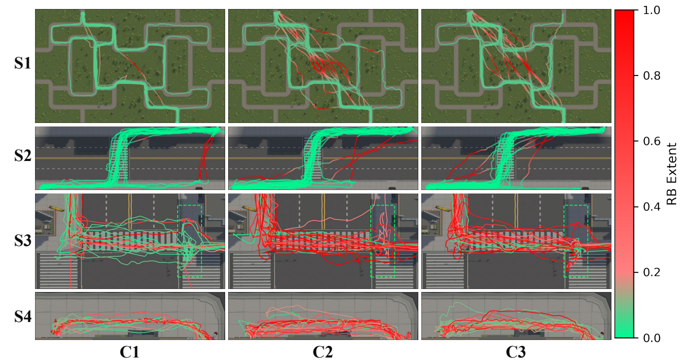

Fig. 4: Participant trajectories across the four scenarios (S1–S4) under the three experimental conditions (C1–C3). Each line represents an individual trajectory, color-coded by the corresponding rule-breaking extent as defined in Sec. 5.1. The dashed boxes in S3 indicate the waiting area.

the results of Kruskal–Wallis tests with Dunn post-hoc comparisons. We additionally report epsilon-squared (ε^2) as an effect size, following Cohen's guidelines [10], interpreted as follows: large (>0.14), medium (>0.06) and small (>0.01).

Large significant condition effects emerged in **S1** ($p < 0.001$, $\varepsilon^2 = 0.244$), **S3** ($p < 0.05$, $\varepsilon^2 = 0.174$), and **S4** ($p < 0.001$, $\varepsilon^2 = 0.207$) scenarios. In all three cases, participants in C2 and C3 exhibited greater rule-breaking than those in C1, while no significant differences were found between C2 and C3. By contrast, the **S2** showed no significant effect of condition ($p = 0.853$), suggesting that participants' behavior remained stable regardless of the proportion of rule-breaking agents.

We assessed cross-scene consistency of participants' rule-breaking extent using Kendall's W, interpreted as small (≈ 0.1), medium (≈ 0.3), and large (≈ 0.5). There was no significant consistency when no RBCs were present ($W = 0.379, \chi^2 = 30.31, p = 0.064$). However, when RBCs were present, the consistency became significant: participants in C3 ($W = 0.548, \chi^2 = 48.20, p = 0.001$) showed stronger consistency than those in C2 ($W = 0.497, \chi^2 = 39.78, p = 0.005$). This indicates a progressively stronger, scene-invariant consistency of individuals' rule-breaking or rule-following behavior as the proportion of RBCs increases.

Table 3: Effect of rule-breaking extent across conditions. Kruskal–Wallis test with Dunn post-hoc (Holm-adjusted p). Effect size reported as epsilon-squared (ε^2).

Scene	Test	Post-hoc
S1	$\chi^2(2) = 17.13,\ p < 0.001,\ \varepsilon^2 = 0.244$	C2 > C1 ($p < 0.001$), C3 > C1 ($p < 0.01$), C2 ≈ C3 ($p = 0.443$)
S2	$\chi^2(2) = 0.319,\ p = 0.853,\ \varepsilon^2 = 0.000$	– (no significant differences)
S3	$\chi^2(2) = 12.80,\ p < 0.01,\ \varepsilon^2 = 0.174$	C2 > C1 ($p < 0.01$), C3 > C1 ($p < 0.05$), C2 ≈ C3 ($p = 0.311$)
S4	$\chi^2(2) = 14.85,\ p < 0.001,\ \varepsilon^2 = 0.207$	C2 > C1 ($p < 0.05$), C3 > C1 ($p < 0.001$), C3 ≈ C2 ($p = 0.143$)

6.2 Participant trajectories

We next examined participants' navigation trajectories across conditions and scenarios. Figure 4 visualizes the recorded paths, with green indicating rule-following and red indicating rule-breaking. In S1 and S2, red trajectories reflected spatial deviations from compliant routes (e.g., cutting across grass or crossing outside the zebra line), more frequent in C2–C3 than in C1 In S3 and S4, where rule-breaking reflected temporal advantages, red trajectories indicate participants who shortened their red-light waiting or bypassed the queue. Overall, these results show that rule-breaking manifested spatially and temporally across social contexts.

6.3 Visual Attention Patterns

We conducted a series of **Mann–Whitney U tests** to compare participants' gaze allocation between rule-following (RF) and rule-breaking (RB) participants across different visual tags, experimental conditions (C1–C3), and scenarios (S1–S4).

Out of 44 comparison groups, 11 showed a statistically significant difference ($p < 0.05$). Notably, the majority of these significant differences (8 out of 11) were related to virtual characters (5 for RFC, 3 for RBC), followed by vehicles (2) and phones (1). This indicates that participants' attention patterns mainly differed when viewing virtual characters. A consistent pattern emerged in most of these character comparisons: RF participants showed significantly more gaze allocation towards RFCs, while RB participants showed greater gaze allocation towards RBCs. So it appears that there was an imitation pattern which led to the decision making of whether to follow or break the rule, where participants would behave according to what they were observing in the scenario. The only exception was found in C3 of S1, where RF participants unexpectedly gazed more at RBCs, with a small significance ($p = 0.03$, $r = 0.45$). Meanwhile, we recorded and labeled the tag of each gazed object in the timeline for each scenario. Figure 5 visualizes S3 gaze data, which shows the most interesting information, enabling detection of jaywalkers who crossed before and after the first RBC. The color coding shows participants' visual attention while waiting and prior to rule-breaking (see deeper discussion in Sec. 7.3). Gaze recording and statistical results are detailed in the supplementary material.

6.4 Post-Experimental Questionnaire

6.4.1 Perception and Experience

We analyzed the questionnaire scores using the same statistical procedure as in Sec. 6.1, applying Kruskal–Wallis tests with Dunn post-hoc comparisons. Figure 6 shows participants' responses to the questionnaire in Table 2. A medium significant difference across conditions was found for **Q2** ($p < 0.05$, $\varepsilon^2 = 0.118$): participants reported greater pressure to break the rule as more agents engaged in rule-breaking. For **Q3**, participants in C2 and C3 showed a tendency toward lower agreement compared to C1, whereas for **Q4**, scores in C2 and C3 tended to be higher. This suggests that observing the rule-breaking made participants less cautious and more inclined to break rules. There was no significant difference for Q1 and Q5, indicating that participants did not perceive negative consequences in VR, nor did they feel safer if others were already breaking the rule. Therefore, in VR, it appears that the imitation factor had more influence than the risk/safety evaluation. The behavior of the virtual agents was reported as natural (Q6) and participants felt immersed and engaged (Q7) with no significant differences across conditions.

6.4.2 Reported Reasons

Figure 7 summarizes participants' self-reported reasons for breaking or following rules across the four scenarios. Rule-breaking was most often attributed to pragmatic considerations such as efficiency (e.g., choosing the shortest path), impatience (e.g., long waiting times), perceived lack of consequences, or even an explicit desire to see what would

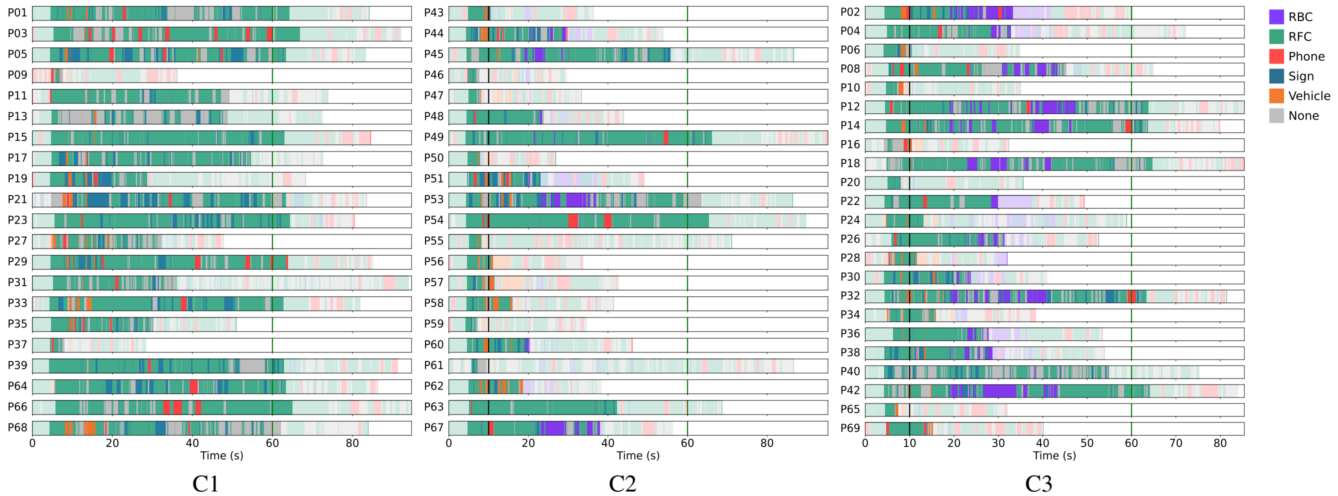

Fig. 5: Eye gaze recording of each participant in S3. Each horizontal bar recorded a participant's gaze target evolution along the time, including both before the participant started to cross (marked by vivid color) and after (marked by fade color), until the participant finished the crossing and left the area (blank). Note that in S3, there are two key time point: 1) At 60s, the traffic light turned green, 2) in C2 and C3, the RBCs initiated jaywalking at 10s. The two time points are respectively marked as green and black dashed lines in the figure.

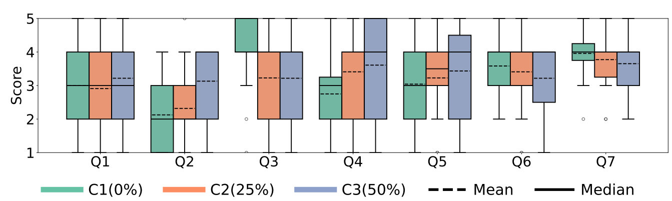

Fig. 6: Results for the Questionnaire in Table 2. The scores are on a 5-Likert scale (1 = strongly disagree, 5 = strongly agree)

happen (exploration). In contrast, rule-following was mainly justified by normative and safety-related factors, including respect for signs, adherence to traffic rules, social norms, and personal habits. These patterns suggest a clear divergence between efficiency-driven motivations for rule-breaking and rule-oriented rationales for rule-following. Imitation emerged as a reason for both behaviors, consistent with the questionnaire responses and the cognitive science literature in Sec. 2.1.

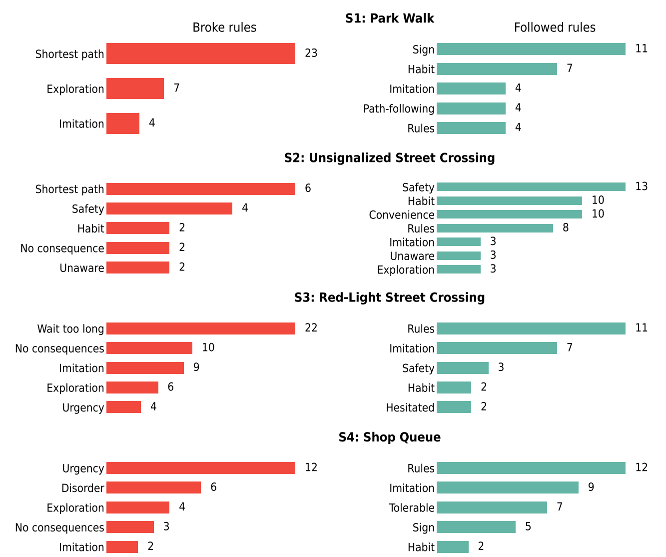

Fig. 7: Labels representing participants' reasons for breaking (in red) or following (in green) rules; Count indicates the number of answers per label. Only labels with counts > 1 are shown.

7 Discussion

7.1 The Drawing Power of Virtual Rule Breakers

Building on previous research, we first hypothesized (**H1**) that the force of social influence exerted by RBCs' would increase with their number, leading to more frequent and extensive rule-breaking by participants [13]. For this reason, we designed three experimental conditions with increasing proportions of rule-breaking. Statistical analysis of rule-breaking (RB) extent showed clear differences in S1, S3, and S4, with C2 and C3 exceeding C1 (see Figure 3). An exception was observed in S2, where no significant difference was found. However, as shown in Figure 4, a clear pattern difference is visible: while rule-breaking participants in C2 and C3 preferred diagonal crossing paths, those in C1 still chose the shortest perpendicular crossing, minimizing exposure to road traffic despite ignoring the zebra-line convention. Participants who exhibited this behavior often explained in their self-reports that they were unaware of the zebra crossing. For example, P9 stated: "*At first I didn't notice there was a zebra crossing... I didn't go back.*" Gaze recordings of those participants showed that before crossing, their attention was frequently on their phones or classified as *None*, suggesting distraction or a focus on the navigation map. Overall, our results suggest that the presence of RBCs in the virtual environment exerts effective social influence, shaping participants' rule-following and rule-breaking decisions in ways consistent with real-world observations. These findings support **H1**, showing that the presence of RBCs significantly increased participants' likelihood of rule-breaking.

Interestingly, the ratio of RBCs did not differ significantly between C2 and C3, consistent with social contagion research suggesting that imitative tendencies increase initially but stabilize as group size grows [13]. The visual comparison in Figure 4 further confirms the similarity in rule-breaking frequency and extent. To interpret this, we refer to previous research on the "drawing power" of real [50] and virtual crowds [37], which found that even simple collective actions, like a group looking up, can strongly influence participants' behavior. Their results showed that as the size of the confederate crowd grew, more participants looked up, but the effect plateaued once the group exceeded about five agents. Our findings suggest a similar marginal effect in rule-breaking scenarios. It is highly possible that the 25% rule-breaker may already surpass this margin, explaining why no significant difference was observed between C2 and C3. We selected ratios of 0%, 25%, and 50% because our study involved free route choice within a large environment. Therefore,

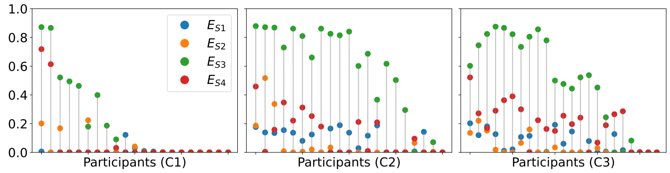

Fig. 8: Rule-breaking extent across the four scenarios. Each dot indicates a participant's rule-breaking score in one scenario. Participants were grouped by condition and ordered by average score.

to ensure participants encountered comparable numbers of RBCs, we opted for sufficiently high scene-level proportions rather than small increments (e.g., 1% or 5%).

7.2 Individual Behavioral Consistency

Figure 8 shows that participants exhibit behavioral consistency across scenarios: those who engaged in high-extent rule-breaking in one scenario tended to do so in others, while rule-followers remained consistent. Statistical tests confirm this pattern, with significant results in C2 and C3 indicating that, although participants were not perfectly uniform across scenarios, their rule-breaking tendencies were strongly consistent. This suggests that participants did not randomly decide whether to follow or break rules in each scene, which is aligned with previous research correlating rule-breaking behavior to personality traits [17, 45]. More interestingly, the effect was stronger in C3 than in C2, indicating that behavioral consistency became more pronounced in situations with a higher number of rule breakers. In C1, however, the statistical test showed a low W score ($W = 0.379$) and a non-significant p-value ($p = 0.064$), indicating that we cannot rule out randomness in participants' rule-following or rule-breaking choices. One explanation is that some participants may have been unwilling to wait for the 60s red light in S3 and therefore chose to jaywalk, consistent with prior research linking jaywalking to longer waiting times, particularly beyond 30s [66]. This may explain the high extent of rule-breaking observed in S3 despite the absence of RBC, while participants still followed rules in other scenarios. Overall, although rule-following and rule-breaking decisions were sometimes scene-specific, participants exhibited a generally consistent tendency. In C2 and C3, several participants never broke the rules despite the presence of RBCs, and one participant even whispered, *"Those people are jaywalking, but I'm not crossing until the green light"*. Figure 5 confirms that participants observed those RBCs, often with prolonged fixations. These participants' choices clearly demonstrated consistency and resistance to rule-breaking influences. We identify two response types: **context-aware imitation**, where decisions adapt to the scene and surrounding agents, and **context ignorance**, where initial tendencies persist despite observing others behaving differently. This aligns with prior work [43].

Considering that $W_{C1} < W_{C2} < W_{C3}$, it is notable that participants' behavior becomes more consistent between rule-breaking and rule-following as the virtual environment grows increasingly chaotic (with more RBCs). From C1 to C3, the RFCs gradually decreased, reducing the social influence encouraging rule-following and possibly allowing participants to act more according to their true intentions rather than conforming to the virtual crowd. Note that this is a preliminary interpretation that warrants further investigation, ideally involving cognitive or psychological experts.

In summary, our results partially support **H2**: although participants' behavior varied across scenarios, they exhibited consistent patterns, particularly as the number of RBCs increased.

7.3 Participant Eye Gaze

Gaze data was used to decode participants' behavior. As shown in Sec. 6.3, despite scene-specific differences, rule-following participants generally focused more time on RFCs, whereas rule-breaking participants focused more on RBCs. Moreover, full gaze recordings enabled finer analysis of attentional focus preceding rule-breaking decisions. We focus our analysis on S3, defined by key time points: the first RBC jaywalking (T=10 s), and the traffic light turning green (T=60 s). In Figure 5, the switch from dark to light color for each horizontal bar indicates when the participant starts crossing the street. The results show that some participants jaywalked within the first 10s (C1: 2 out of 21, C2: 4 out of 21, C3: 3 out of 23), before observing RBCs in C2 and C3. Conversely, several participants in C3 waited for the green light despite 50% of surrounding characters breaking the rules. These observations support the **context ignorance** response discussed in Sec 7.2. We next focus on C2 and C3, examining participant behavior between the first RBC jaywalking and the traffic light turning green. In C2, 12 participants jaywalked during this time window, of which 4 were looking at the RBCs when they started moving, while 8 did not fixate on them. In C3, 7 out of 15 participants were looking at the RBCs when they started crossing, and 6 were looking at cars, which is aligned with previous research which also reported higher fixations towards dangerous hazards [19]. Note that in S1, the RBCs were not presented; yet, 7 participants performed jaywalking within the same time window. We believe this interesting observation confirms that the social influence of the RBCs indeed drove some participants' jaywalking behavior, while others could simply be driven by personality traits driving lack of patience or by not perceiving danger or negative consequences. Our results provide preliminary validation for **H3**. This study marks one of the first attempts to systematically collect and analyze pedestrian gaze data, specifically examining its relationship to rule-breaking behavior. In the absence of established metrics and analytical frameworks, our foundational methods nonetheless provide valuable insights and lay the groundwork for future research.

7.4 Behavioral Ecological Validity

Although VR has been used to study imitation in human crowds [37, 60], daily rule-breaking scenarios remain unexplored. Our work goes beyond the state-of-the-art, representing the first attempt to address this gap. The validation of **H1** and partial validation of **H2** successfully confirm that our VR experiment captures participant behaviors consistent with findings from previous real-world field observations [27]. Previous work on ecological validity [25] reported from real world observations that pedestrians are 1.5 to 2.5 times more likely to jaywalk on a red light if they observe a neighbor starting to cross, which is consistent with the results observed in our VR experiment for S3, with probabilities increasing by 1.5 in C2 and by 2 in C3. In addition, although this work does not aim to discover participants' psychological and cognitive mechanisms, the subjective evaluations provide valuable insights. Figure 7 shows that time-saving is the most cited reason for rule-breaking, whereas safety and rules are the main concerns for rule-following, consistent with everyday observations [25]. Note that in the two street-crossing scenarios (S2 and S3), both RB and RF participants cited *safety*, indicating that they evaluated the danger of their movements in the virtual situations, even though ultimately they reached different conclusions and took opposite actions. Notably, the terms "*no consequence*" and "*exploration*" appeared exclusively in the responses of the RB participants. We believe this reflects an interesting pattern: RB participants might self allow to perform actions to fulfill personal interest, whereas RF participants explored the environment while still adhering to social rules. For example, taking longer paths in the park to avoid stepping on the grass (see S1, C1, in Figure 4). These observations indicate that our experiment produced results qualitatively consistent with real-world studies. While a real-world replication could provide stronger validation, ethical and safety concerns could make it infeasible for some scenarios. VR experiments, by contrast, offer greater control and replicability, provided that the virtual environment is perceived as plausible by the participant [63].

Post-experimental questionnaires provided practical insights into how participants' experiences varied across conditions. As the proportion of RBCs increased, participants reported greater pressure, lower safety, reduced perceived realism and decreased immersion. These effects may partly stem from limitations in the crowd simulation, as classical models struggle with chaotic scenarios, leading to less coherent and less plausible crowd behavior.

8 Limitations and Insights

To fully exploit VR for studying human behavior, environments and events must be plausible and elicit a strong sense of presence [63]; otherwise, participants' behavior may not replicate real-world behavior. From the open-ended questionnaires, we gathered information about user experience and areas for improvement. For example, the animations used for the virtual characters when performing non-normative behavior need to exhibit more interaction, such as gazing towards other non-normative characters. Moreover, the tendencies observed in Q6 and Q7 suggest that an excess of RBCs may reduce participants' perception of realism and immersion. However, observing a small number of rule-breaking characters could improve immersion, according to participants' comments. For example, in C1 (0% RBC), P27 mentioned: *"I didn't see any agents breaking the rules, maybe increase the possibility of them doing so, because it is quite common."*. In our experiments, the proportion of rule breakers was established ad hoc. Future studies should consider more balanced mixtures of rule-following and rule-breaking behaviors to ensure socially believable crowds. Based on our findings, we suggest keeping the proportion of rule-breaking characters below 25%. Traffic simulation may also have influenced participants' risk assessment; for example, P39 noted: *"car density could greatly influence the decision to break or not break the rules"*. Future work may thus include advanced traffic simulation for improved risk perception evaluation.

At the time of our experiment, motion matching combined with a force-based crowd simulation offered the most controllable and effective animation approach. However, its perceptual realism remained limited for some participants (e.g., P14: *"sometimes the pedestrians' postures were a bit odd (one person's running posture was really funny)"*. Rule-breaking by RBCs was explicitly scripted, except in Scenario S3, where we used the OMC framework to prerecord animations capturing contagion effects such as rule-breaking, hesitation, and traffic observation. In our simulation, virtual agents do not socially react to the user's violations (e.g., by casting disapproving glares, gesturing) or exhibit behavioral contagion. While this design isolates the imitation effect from social confrontation, future work could incorporate reactive behaviors (e.g., gaze, verbal objections) to study the impact of social sanctioning on rule-breaking. Additionally, analyzing the effects of virtual authority figures could inform city planners in optimizing police presence across scenarios. In our experiment, we decided to use a fixed scenario order to avoid confounds from environment modifications, but it may have introduced learning effects in later scenarios; however, participants did not comment on any perceived patterns in rule-breaking behavior across scenarios.

Finally, this study aimed to test the behavioral ecological validity of rule-breaking in VR to inform future crowd simulation models. While our experiment validated the social imitation effects observed in the real world, conclusions about human behavior must be tempered by the limitations of VR and the specific social background of our participants. Results may differ with samples from other geographical or social contexts.

9 Conclusion

In this work, we studied user responses to virtual characters' rule-breaking in everyday crowd scenarios using immersive VR. Across four scenarios, we varied the proportion of RBCs and analyzed participants' rule-breaking behavior. Our results show that participants' decisions were influenced by the presence of RBCs.

Individual factors played a key role: gaze allocation revealed that users' environmental scanning and attention to characters correlated with their rule-breaking behavior. Subjective reports further showed that observing others' violations reduced perceived risks and increased the legitimacy of rule-breaking. Furthermore, the eye gaze data contributed to the confirmation that RBCs indeed triggered participants' rule breaking, and it also enabled cross-verification of the participants' subjective reports. Our results also suggest that, 25% RBCs in a free route choice scenario can provide effective social influences. Meanwhile, the effectiveness of even lower RBC ratios would be worth exploring in the future.

We provide insights into both the research on rule-breaking using VR and crowd simulation. This work validates VR in the study of everyday rule-breaking while opening multiple research questions that require further interdisciplinary knowledge, especially in psychology and cognitive science.

Acknowledgments

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References

[1] G. Allon and E. Hanany. Cutting in line: Social norms in queues. *Manag. Sci.*, 58:493–506, 2012. 2

[2] C. Armbrüster, M. Wolter, T. Kuhlen, W. Spijkers, and B. Fimm. Depth Perception in Virtual Reality: Distance Estimations in Peri- and Extrapersonal Space. *CyberPsychology & Behavior*, 11(1):9–15, Feb. 2008. doi: 10.1089/cpb.2007.9935 2

[3] S. E. Asch. Opinions and social pressure. *Nature*, 176:1009–1011, 1955. 2

[4] S. E. Asch. Studies of independence and conformity: I. a minority of one against a unanimous majority. *Psychological monographs: General and applied*, 70(9):1, 1956. 1, 2

[5] J. N. Bailenson, J. Blascovich, A. C. Beall, and J. M. Loomis. Equilibrium theory revisited: Mutual gaze and personal space in virtual environments. *Presence: Teleoperators & Virtual Environments*, 10(6):583–598, 2001. 2

[6] F. Berton, L. Hoyet, A.-H. Olivier, J. Bruneau, O. L. Meur, and J. Pettré. Eye-gaze activity in crowds: Impact of virtual reality and density. *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 322–331, 2020. 2

[7] J. Bruneau, A.-H. Olivier, and J. Pettre. Going through, going around: A study on individual avoidance of groups. *IEEE transactions on visualization and computer graphics*, 21(4):520–528, 2015. 2

[8] D. K. Campbell-Meiklejohn, D. R. Bach, A. Roepstorff, R. J. Dolan, and C. D. Frith. How the opinion of others affects our valuation of objects. *Current Biology*, 20(13):1165–1170, 2010. 2

[9] R. B. Cialdini, R. R. Reno, and C. A. Kallgren. A focus theory of normative conduct: Recycling the concept of norms to reduce littering in public places. *Journal of Personality and Social Psychology*, 58:1015–1026, 1990. 2

[10] J. Cohen. *Statistical power analysis for the behavioral sciences*. routledge, 2013. 6

[11] R. Collins. *Violence: A micro-sociological theory*. Princeton University Press, 2008. 2

[12] T. Connolly and L. Åberg. Some contagion models of speeding. *Accident Analysis & Prevention*, 25(1):57–66, 1993. 2

[13] E. Cracco and M. Brass. The role of sensorimotor processes in social group contagion. *Cognitive Psychology*, 103:23–41, 2018. 1, 2, 7

[14] E. Cracco, L. De Coster, M. Andres, and M. Brass. Motor simulation beyond the dyad: Automatic imitation of multiple actors. *Journal of Experimental Psychology: Human Perception and Performance*, 41(6):1488, 2015. 2

[15] E. Cracco, L. De Coster, M. Andres, and M. Brass. Mirroring multiple agents: Motor resonance during action observation is modulated by the number of agents. *Social Cognitive and Affective Neuroscience*, 11(9):1422–1427, 2016. 2

[16] E. Cracco, C. Keysers, A. Clauwaert, and M. Brass. Representing multiple observed actions in the motor system. *Cerebral Cortex*, 29(8):3631–3641, 2019. 2

[17] L. Cubillos-Pinilla and F. Emmerling. Taking the chance!–interindividual differences in rule-breaking. *PloS One*, 17(10):e0274837, 2022. 8

[18] T. P. Davies, H. M. Fry, A. G. Wilson, and S. R. Bishop. A mathematical model of the london riots and their policing. *Scientific reports*, 3(1):1303, 2013. 2

[19] C. de Juan-Ripoll, J. Llanes-Jurado, I. A. C. Giglioli, J. Marín-Morales, and M. Alcañiz. An immersive virtual reality game for predicting risk taking through the use of implicit measures. *Applied Sciences*, 11(2):825, 2021. 2, 8

[20] T. Deguchi. A simulation of rule-breaking behavior in public places. *Social Science Computer Review*, 32(4):439–452, 2014. 2

[21] M. Deutsch and H. B. Gerard. A study of normative and informational social influences upon individual judgment. *The journal of abnormal and social psychology*, 51(3):629, 1955. 2

[22] M. F. Dold and M. Khadjavi. Jumping the queue: An experiment on procedural preferences. *Games Econ. Behav.*, 102:127–137, 2017. 2

[23] X. Du, J. Ma, M. Zhang, J. Wang, and C. Liang. The attentional guidance and facilitating effects of group behavioral cues on individual college pedestrians' jaywalking decisions. *Traffic Injury Prevention*, 25:733 – 740, 2024. 1, 2

[24] J. M. Epstein. Modeling civil violence: An agent-based computational approach. *Proceedings of the National Academy of Sciences*, 99(suppl_3):7243–7250, 2002. 2

[25] J. J. Faria, S. Krause, and J. Krause. Collective behavior in road crossing pedestrians: the role of social information. *Behavioral ecology*, 21(6):1236–1242, 2010. 8

[26] Y. Feng, D. C. Duives, W. Daamen, and S. P. Hoogendoorn. Data collection methods for studying pedestrian behaviour: A systematic review. *Building and Environment*, 2021. 2

[27] O. Genschow and E. Cracco. *Automatic imitation*. Springer Nature, 2025. 8

[28] M. Gérin-Lajoie, C. L. Richards, J. Fung, and B. J. McFadyen. Characteristics of personal space during obstacle circumvention in physical and virtual environments. *Gait & posture*, 27(2):239–247, 2008. 2

[29] M. Germar, A. Schlemmer, K. Krug, A. Voss, and A. Mojzisch. Social influence and perceptual decision making: A diffusion model analysis. *Personality and Social Psychology Bulletin*, 40(2):217–231, 2014. 2

[30] M. Giannoulaki and Z. Christoforou. Pedestrian walking speed analysis: A systematic review. *Sustainability*, 16(11):4813, 2024. 3

[31] E. Goh. Walking off-trail in national parks: Monkey see monkey do. *Leisure Sciences*, 45(1):1–23, 2023. 2

[32] M. S. Granovetter. Threshold models of collective behavior. *American Journal of Sociology*, 83:1420 – 1443, 1978. 2

[33] N. Guéguen and N. Pichot. The influence of status on pedestrians' failure to observe a road-safety rule. *The Journal of Social Psychology*, 141:413 – 415, 2001. 2

[34] M. Haghani and M. Sarvi. Crowd behaviour and motion: Empirical methods. *Transportation Research Part B-methodological*, 107:253–294, 2018. 2

[35] D. Helbing and P. Molnar. Social force model for pedestrian dynamics. *Physical review E*, 51(5):4282, 1995. 3

[36] L. Huang, G. Cai, H. Yuan, and J. Chen. From public gatherings to the burst of collective violence: An agent-based emotion contagion model. In *2018 IEEE international conference on intelligence and security informatics (ISI)*, pp. 193–198. IEEE, 2018. 2

[37] E. M. Jorjafki, B. J. Sagarin, and S. Butail. Drawing power of virtual crowds. *Journal of The Royal Society Interface*, 15(145):20180335, 2018. 7, 8

[38] K. Keizer, S. Lindenberg, and L. Steg. The spreading of disorder. *Science*, 322:1681 – 1685, 2008. 2

[39] E. A. Khuzam, G. Lanzaro, and T. Sayed. Impact of jaywalking on pedestrian interaction behavior: A multiagent markov game-based analysis. *Accident; analysis and prevention*, 220:108141, 2025. 2

[40] M. Kinateder, E. Ronchi, D. Gromer, M. Müller, M. Jost, M. Nehfischer, A. Mühlberger, and P. Pauli. Social influence on route choice in a virtual reality tunnel fire. *Transportation Research Part F-traffic Psychology and Behaviour*, 26:116–125, 2014. 2

[41] M. Kinateder and W. H. Warren. Social influence on evacuation behavior in real and virtual environments. *Frontiers Robotics AI*, 3:43, 2016. 2

[42] A. Koilias, M. G. Nelson, C.-N. Anagnostopoulos, and C. Mousas. Immersive walking in a virtual crowd: The effects of the density, speed, and direction of a virtual crowd on human movement behavior. *Computer Animation and Virtual Worlds*, 31(6):e1928, 2020. 2

[43] J. Krause, P. Romanczuk, E. Cracco, W. Arlidge, A. Nassauer, and M. Brass. Collective rule-breaking. *Trends in Cognitive Sciences*, 25(12):1082–1095, 2021. 1, 2, 4, 8

[44] B. Latané. The psychology of social impact. *American Psychologist*, 36:343–356, 1981. 2

[45] I. Lebuda, M. Karwowski, A. J. R. Galang, G. Szumski, and A. Firkowska-Mankiewicz. Personality predictors of creative achievement and lawbreaking behavior. *Current Psychology*, 40(8):3629–3638, 2021. 8

[46] M. M. Lefkowitz, R. R. Blake, and J. S. Mouton. Status factors in pedestrain violation of traffic signals. *Journal of abnormal psychology*, 51 3:704–6, 1955. 2

[47] J. Llobera, B. Spanlang, G. Ruffini, and M. Slater. Proxemics with multiple dynamic characters in an immersive virtual environment. *ACM Transactions on Applied Perception (TAP)*, 8(1):1–12, 2010. 2

[48] J. M. Loomis, J. M. Knapp, et al. Visual perception of egocentric distance in real and virtual environments. *Virtual and adaptive environments*, 11:21–46, 2003. 2

[49] R. McDonnell, M. Breidt, and H. H. Bülthoff. Render me real? investigating the effect of render style on the perception of animated virtual humans. *ACM Transactions on Graphics (TOG)*, 31(4):1–11, 2012. 3

[50] S. Milgram, L. Bickman, and L. Berkowitz. Note on the drawing power of crowds of different size. *Journal of personality and social psychology*, 13(2):79, 1969. 2, 7

[51] R. Morris, M. Kotitsa, J. Bramham, B. Brooks, and F. Rose. Virtual reality investigation of strategy formation, rule breaking and prospective memory in patients with focal prefrontal neurosurgical lesions. In *Proceedings of the 4th International Conference on Disability, Virtual Reality & Associated Technologies*, pp. 18–21, 2002. 2

[52] C. Mousas, A. Koilias, D. Anastasiou, B. Rekabdar, and C.-N. Anagnostopoulos. Effects of self-avatar and gaze on avoidance movement behavior. In *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pp. 726–734. IEEE, 2019. 2

[53] M. Moussaïd, M. Kapadia, T. Thrash, R. W. Sumner, M. Gross, D. Helbing, and C. Hölscher. Crowd behaviour during high-stress evacuations in an immersive virtual environment. *Journal of The Royal Society Interface*, 13(122):20160414, 2016. 2

[54] M. Nelson, A. Koilias, S. Gubbi, and C. Mousas. Within a virtual crowd: Exploring human movement behavior during immersive virtual crowd interaction. In *Proceedings of the 17th ACM SIGGRAPH International Conference on Virtual-Reality Continuum and its Applications in Industry*, pp. 1–10, 2019. 2

[55] T. Newburn, K. Cooper, R. Deacon, and R. Diski. Shopping for free? looting, consumerism and the 2011 riots. *British Journal of Criminology*, 55(5):987–1004, 2015. 2

[56] B. Pires and A. T. Crooks. Modeling the emergence of riots: A geosimulation approach. *Computers, Environment and Urban Systems*, 61:66–80, 2017. 2

[57] J. L. Ponton, H. Yun, C. Andujar, and N. Pelechano. Combining motion matching and orientation prediction to animate avatars for consumer-grade vr devices. In *Computer Graphics Forum*, vol. 41, pp. 107–118. Wiley Online Library, 2022. 3

[58] P. Raimbaud, A. Jovane, K. Zibrek, C. Pacchierotti, M. Christie, L. Hoyet, J. Pettré, and A.-H. Olivier. The stare-in-the-crowd effect when navigating a crowd in virtual reality. *ACM Symposium on Applied Perception 2023*, 2023. 2

[59] R. S. Renner, B. M. Velichkovsky, and J. R. Helmert. The perception of egocentric distances in virtual environments-a review. *ACM Computing Surveys (CSUR)*, 46(2):1–40, 2013. 2

[60] A. Ríos and N. Pelechano. Follower behavior under stress in immersive vr. *Virtual Reality*, 24(4):683–694, 2020. 1, 2, 8

[61] T. Rosenbloom. Crossing at a red light: Behaviour of individuals and groups. *Transportation Research Part F-traffic Psychology and Behaviour*, 12:389–394, 2009. 1, 2

[62] P. A. Singleton, M. Mekker, S. Boyer, et al. Pedestrian traffic signal violations: Safety, design, and operational implications. Technical report, Utah. Dept. of Transportation. Division of Research, 2023. 2

[63] M. Slater. Immersion and the illusion of presence in virtual reality. *British journal of psychology*, 109(3):431–433, 2018. 2, 8, 9

[64] M. Slater, A. Rovira, R. Southern, D. Swapp, J. J. Zhang, C. Campbell, and M. Levine. Bystander responses to a violent incident in an immersive virtual environment. *PloS one*, 8(1):e52766, 2013. 2

[65] H. Trivedi and C. Mousas. Human-virtual crowd interaction: Towards understanding the effects of crowd avoidance proximity in an immersive virtual environment. *Computer Animation and Virtual Worlds*, 34(3-4):e2169, 2023. 2

[66] C. Vallyon, S. Turner, and S. Hodgson. *Reducing pedestrian delay at traffic signals*. Number 440. NZ Transport Agency, 2011. 8

[67] P. Willemsen, M. B. Colton, S. H. Creem-Regehr, and W. B. Thompson. The effects of head-mounted display mechanics on distance judgments in virtual environments. In *Proceedings of the 1st Symposium on Applied Perception in Graphics and Visualization*, pp. 35–38, 2004. 2

[68] J. Q. Wilson and G. L. Kelling. Broken windows. 1982. 2

[69] T. Yin, L. Hoyet, M. Christie, M.-P. Cani, and J. Pettré. The one-man-crowd: Single user generation of crowd motions using virtual reality. *IEEE*

Transactions on Visualization and Computer Graphics, 28(5):2245–2255, 2022. 2, 4

[70] T. Yin, L. Hoyet, M. Christie, M.-P. Cani, and J. Pettré. With or without you: Effect of contextual and responsive crowds on vr-based crowd motion capture. *IEEE Transactions on Visualization and Computer Graphics*, 30:2785–2795, 2024. 2

[71] H. Yun, J. L. Pontón, A. Beacco, C. Andújar, and N. Pelechano. Exploring the role of expected collision feedback in crowded virtual environments. *2024 IEEE Conference Virtual Reality and 3D User Interfaces (VR)*, pp. 472–481, 2024. 2

[72] J. Zaki, J. Schirmer, and J. P. Mitchell. Social influence modulates the neural computation of value. *Psychological science*, 22(7):894–900, 2011. 2