Realism Drives Interpersonal Reciprocity but Yields to AI-Assisted Egocentrism in a Coordination Experiment

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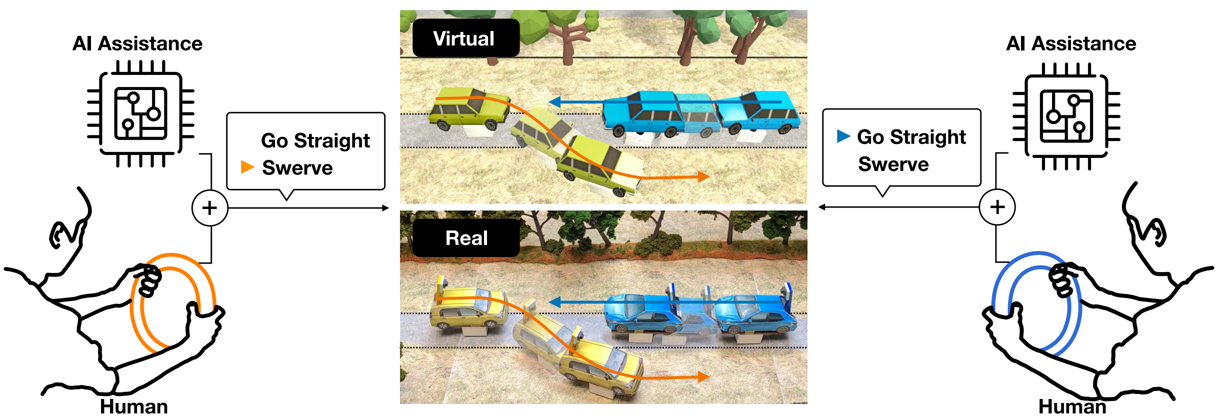

Figure 1: Experiment examining the effects of realism and AI assistance on interpersonal coordination.

Abstract

Virtual reality technologies that enhance realism and artificial intelligence (AI) systems that assist human behavior are increasingly interwoven in social applications. However, how these technologies might jointly influence interpersonal coordination remains unclear. We conducted an experiment with 240 participants in 120 pairs who interacted through remote-controlled robot cars in a physical space or virtual cars in a digital space, with or without autosteering assistance, using the chicken game, an established model of interpersonal coordination. We find that both realism and AI assistance help improve user performance but through opposing mechanisms. Real-world contexts enhanced communication, fostering reciprocal actions and collective benefits. In contrast, autosteering assistance diminished the need for interpersonal coordination, shifting participants' focus towards self-interest. Notably, when combined, the egocentric effects of autosteering assistance outweighed the prosocial effects of realism. The design of HCI systems that involve social coordination will, we believe, need to take such effects into account.

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CCS Concepts

• **Human-centered computing** → **Empirical studies in collaborative and social computing**.

Keywords

social coordination, realism, AI assistance, human agency, experiments

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1 Introduction

In the rapidly evolving landscape of human-computer interaction (HCI), two emerging trends are reshaping how people interact and coordinate with one another: *varying levels of realism in relevant interaction environments* and *artificial intelligence (AI) assistance into individual decision-making*. On the one hand, advancements in virtual and augmented reality (VR/AR) technologies are increasingly blurring the line between real and virtual environments [30, 44, 84]. For instance, these technologies enable users to engage in social coordination within digital spaces that simulate or even surpass physical reality[10]. On the other hand, automation and AI systems are being integrated into social interactions, both real and virtual[1, 39, 72]. For example, tools like driving assistance, AI-driven recommendations, and automated communication systems can support or even replace human decision-making in contexts that require social coordination [82].

Together, these advancements are transforming how people work, collaborate, and make decisions across a range of interaction contexts. Virtual environments now serve as common platforms for hosting human social behavior, including social behavior with AI agent participants [58, 63, 67, 77]. AI systems are also deeply embedded in interpersonal communication and coordinated activities, particularly within digital spaces, where they can enhance or streamline interactions[22, 66, 78, 80, 81]. Meanwhile, many real-world social interactions are augmented by digital technologies[3], such as driving assistance, robotic navigation, and bio-instrumentation, building on the success of virtual platforms that have long deployed AI features.

As the virtuality-reality continuum [35] and human-AI integration converge across various HCI applications, a critical question arises: How might realism and AI assistance *interact* to shape social coordination? The effects of realism and AI assistance on human social behavior have been studied independently, with the assumption that each improves (or affects) user performance and that their combination would yield compounded benefits. However, it remains unclear whether these factors independently exert these effects or whether one overshadows the other. Addressing this question is essential for designing HCI systems that effectively integrate both realism and AI assistance while supporting the goals of social coordination.

We therefore examine both *realism* and *AI assistance* simultaneously, a combination rarely explored in HCI research but crucial to understanding their comprehensive impact on social coordination. To achieve this, we developed an experimental system where participants (N=240 in 120 dyads) interact remotely through robotic vehicles located in a physical space, creating an interaction context of high realism. We also implemented a comparable virtual context where participants interact with virtual vehicles in a digital space. Both systems were used in a human-subject experiment involving the "chicken game" [73, 106] — a widely studied social coordination model set within a driving scenario. We incorporated two additional factors into the coordination task: a basic driving assistance system (autosteering before collisions; Level 1 as defined by the Society of Automotive Engineers [18]) and a messaging function. In sum, our experiment followed a $2 \times 2 \times 2$ design, with three independent variables: "interaction context" (real or virtual environment), "AI assistance" (presence or absence of autosteering assistance), and "communication capability" (presence or absence of the messaging function).

We used the chicken game as the study system due to its relevance to real-world coordination contexts where individuals must navigate conflicting incentives [95]. For instance, in manual and even semi-autonomous driving, drivers must balance personal goals (e.g., reaching their destination quickly) with cooperative behaviors that ensure safety for others (e.g., yielding at intersections or during lane changes) [78, 82, 94, 106]. Similarly, in teamwork studies, individuals often operate within shared virtual and physical spaces, requiring them to balance self-interest with collaboration to achieve collective outcomes[41, 96, 100]. These scenarios illustrate the tension between self-interest and reciprocity plays a critical role in shaping interactions, whether real or virtual.

The driving coordination scenario exemplified by the chicken game is particularly useful for systematically controlling the reality-virtual continuum and human-AI integration. By focusing on object-mediated interactions (e.g., vehicles), we avoid the complexities involved in designing comparable virtual human avatars (with possible complications related the uncanny valley[55]), enabling rigorous comparisons between real and virtual settings. In addition, driving assistance technology is one of the most prevalent AI systems today, allowing participants to engage without requiring extensive training or unfamiliarity with the task. Overall, the chicken game provides an abstract yet robust framework for systematically addressing our research questions.

Our findings indicate that realism and AI assistance both enhance user performance and experience in social coordination but through opposing mechanisms. As a result, when combined, the influence of AI assistance overshadows that of realism in shaping social coordination, preventing the compounded effects that one might intuitively expect.

More particularly, study participants who interacted in a real-world space experienced fewer conflicts and engaged more in reciprocal actions through communication than those who interacted in a virtual space. In contrast, the introduction of driving assistance significantly hindered reciprocal actions among participants (even while reducing collisions). Importantly, the positive impacts of realism on reciprocity diminished when AI assistance was introduced. This suggests that while enhancing realism supports social coordination under certain conditions, it cannot sustain effective AI-assisted social interactions. In other words, in systems where AI handles essential decision-making or coordination, investing in ultra-realistic environments may yield limited benefits in enhancing social behavior. In addition, while interpersonal communication is widely recognized to enhance social coordination, our results indicate that this effect occurs primarily in realistic settings and in the absence of AI assistance. This also underscores the role of realism in boosting communication effectiveness: in real contexts, users may rely more on subtle social cues for coordination – an effect less prominent when they know they are interacting in artificial environments.

Although model-based experimental results should not be overgeneralized, these insights underline the importance of understanding the nuanced effects of realism and AI assistance in designing interactive systems. By recognizing the conditions under which these factors enhance or hinder social coordination, we can develop more effective HCI applications that better support human reciprocity and interaction. We conclude by providing a design matrix that serves as a practical guide for designing social interaction systems, highlighting the impacts of realism and AI assistance on collective performance and user experience.

2 Related Work

Three research threads are closely related to the topic of this paper: social coordination, enhancing realism, and AI assistance in human decision-making.

2.1 Social Coordination

Social coordination, the process by which individuals align their actions to achieve a shared goal, is fundamental to designing effective interactions in HCI contexts, from online collaboration to daily driving [32, 41, 49, 71, 82, 94, 106]. For instance, Kraut et al. [41] and Preece [71] demonstrate how social coordination is essential for online communities and provide design guidance to enhance it through turn-taking, shared understanding, and common objectives. Gutwin and Greenberg discuss the role of workspace awareness in supporting coordination and reciprocal actions, providing a framework for real-time groupware design [32]. Schwarting et al. highlights the variation in human driving styles in various lane-changing scenarios, emphasizing the need for autonomous vehicles to adapt to such diverse intentions of human drivers on shared roads [78].

A key component of social coordination is norms of reciprocity, which involve the expectation of mutual exchanges of actions and concessions [11, 24, 25, 31, 92]. For reciprocity to occur, one party must initially yield to the other, followed by a role reversal in subsequent interactions. Effective coordination depends on understanding and anticipating the actions of others, a process deeply rooted in our agency in decision-making and our perceptions of the environment in which these interactions occur [49]. Communication plays a crucial role in establishing shared understanding. Even brief conversations can help people overcome collective action challenges [19, 51]. Without effective communication, people are more likely to have conflicts, which is the worst outcome of social coordination.

Social coordination challenges and solutions have been extensively studied using economic games based on game theory [9, 11, 64, 73]. Economics games refer to a theoretical and empirical setting where individuals interact under given options and earn rewards based on the interactions [13, 85]. Studies have shown that an individual's decisions in various economic games correlate with one another and with real-life coordination behaviors [69]. The standardization of many game settings and measurements allows researchers to study social behaviors systematically [26, 34, 90, 101] and apply these insights to HCI contexts [23, 37, 48, 80, 82, 106]. For instance, Erlei et al. applied the ultimate bargaining game to an HCI context to show strong human preferences against automated agents in their decision-making regarding resource allocation [23]. Zhang et al. used online surveys to investigate human drivers' responses to coordination challenges modeled by the chicken and public goods games when interacting with both autonomous and human-driven cars [106]. Building on this rich tradition in behavioral sciences and HCI, our work uses an economic game experiment to explore new dimensions of social coordination: realism and AI assistance.

2.2 Enhancing Realism

Virtual environments have been developed to replicate real-world settings, providing users with simulated experiences that mimic and even enhance physical reality. This approach has been instrumental in a range of applications, such as training simulations, virtual collaborations, and simulation games. By creating controlled and replicable settings, these virtual environments offer a platform for realizing various aspects of human behavior in a manner that would be difficult or impractical to achieve in the real world [6, 10, 58].

A substantial body of HCI research has explored how human performance differs between virtual and real-world environments. For instance, Bowman and McMahan found that task performance in virtual environments can be significantly affected by factors such as the fidelity of the virtual interface and user interaction methods [8]. Godley et al. discuss using driving simulators to find that people drove similarly with real and virtual cars, albeit significantly slower in the simulators [28]. Podkosova, Kaufmann [70], and Buck et al. [12] demonstrated that spatial navigation and situational awareness differ between virtual reality (VR) and real-world conditions, impacting coordinated movements among users, suggesting that people might need larger personal space in virtual environments.

Recent technological advancements have enhanced the realism of virtual environments, increasing users' sense of presence and reality [30, 44, 84]. Technologies such as high-fidelity graphics, immersive audio, and sophisticated haptic feedback have contributed to making simulated experiences more realistic. The impact of such enhanced realism on user behavior and performance is an important and growing area of interest in various HCI applications [65, 75, 93]. For example, Roger et al. found that high-fidelity graphics improve player experience in object manipulation tasks, while moderate realism suffices for whole-body movements [74]. Weiß et al. highlighted that higher image realism in safety-critical situations can increase users' stress responses, indicating that realism influences psychological and behavioral outcomes [97]. Chan et al. showed that participants who experienced immersive virtual nature improved pro-environmental attitudes and wanted to engage with real nature, suggesting that realism can increase authenticity and interest in interaction subjects [14].

Our work extends this line of research by conducting a rigorous experimental comparison of human social behavior in an interaction environment that participants perceive as real and an identical virtual world. We also examine the impact of realism on social interaction involving AI assistance, where humans, as the agents perceiving the interaction context, lack full agency over their behavior.

2.3 AI-Integrated Decision-Making

Recent developments in AI assistance and automation have introduced another dimension to social coordination. Machines now make autonomous decisions, sense their environments, and suggest actions to human users. Research examining interactions between autonomous AI and humans includes hybrid systems, which handle collective behavior manifesting from interactions among many machines and humans [72]. There are also studies on human-agent collectives [39] and engineering prosociality through autonomous agents [66, 80, 81].

However, an intermediate state can exist between machine intelligence and human agents, where a single entity integrates both human and AI autonomy [102]. People integrate such machine intelligence into their decision-making, such as driving cars equipped with active safety assistance [5, 16], enhancing body manipulation through biosignal stimulation [45], or using suggestions from generative AI for writing and coding [62, 68]. This integration creates what is called shared or hybrid autonomy, which refers to the mixed decision-making between humans and automated systems within a single entity (or group)[38, 61, 105]. For instance, driving behavior by human drivers with safety assistance can be seen as a product of shared autonomy, combining human judgment and machine intelligence.

Hybrid autonomy should be considered not only in driving scenarios but also in human augmentation, robotic body control, and any setup where machine intelligence and humans engage in integrated actions [20]. Previous studies have investigated how shared autonomy affects individual subjectivity, such as an individual's sense of control of a computer cursor movement that is automatically corrected [99], robot control with autonomous AI [15], and the sense of agency when users' bodies are driven by electric muscle stimulation that might override their judgment and movement [91].

To understand specifically social behavior in such hybrid autonomy, it is necessary to consider a framework that takes into account the subjectivity mutually recognized by each participant [11, 24, 31]. Previous work also examines how AI assistance can both enhance and impede user prosocial behavior [48, 66, 72, 80, 81]. For example, Shirado et al. demonstrate that automation can help users communicate and coordinate with each other when it supports their decision-making [82]. However, when automated systems take over users' agency, it can reduce the need for social engagement, potentially leading to excessive dependence on automated systems and decreased reciprocal coordination. Together, comprehensive understanding of the impact of realism and AI assistance on social behavior is crucial to grasp the general influence of HCI on social coordination.

3 Problem Settings and Research Questions

We investigate how realism influences AI-assisted social coordination using a game-theoretic model called the "chicken game" [73]. Also referred to as the snowdrift game or the hawk-dove game [86, 89], this interaction model has been widely applied to various physical coordination problems, such as intersection crossing, lane changing, and expressway merging [78, 94, 106], as well as to social dilemmas like resource management and negotiation stalemates [9, 47]. Although we used a driving coordination scenario of the chicken game, our interest is not in the specifics of driving systems, but rather in how humans respond to the general coordination challenge when influenced by realism and AI assistance.

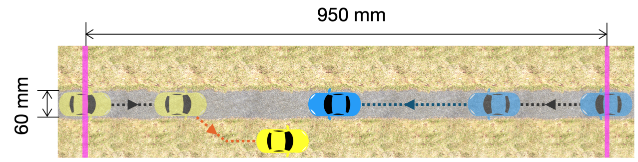

Figure 2: Interaction setup of the chicken game. Two cars start facing each other on a single road. Each car aims to reach its designated goal (marked by pink lines) as quickly as possible to maximize its benefit. However, if a car swerves off the road to avoid a collision, its driving speed is reduced by 75%, incurring a cost. The travel distance toward its goal (indicated by the black and blue dot lines) is considered the player's self-reward. Meanwhile, the distance their counterpart covers while they are off the road is regarded as the reward given to the other. In this example, when the yellow car goes off-road (indicated by the orange dot line), it helps the blue car earn rewards based on the blue car's travel distance during that time (indicated by the blue dot line).

Table 1: Payoff structure of the chicken game. The quantity b indicates the maximum possible benefit when a focal actor drives the road from start to finish without obstacles. And c indicates the cost of losing time and the additional effort related to manually swerving off the road. The benefit b is larger than the cost c. When both actors seek to maximize their payoff, they will collide, creating the worst outcome.

		Your counterpart: Go straight	Your counterpart: Swerve
You	Go straight	0	b
	Swerve	b - c	b - c

We use a version of the chicken game where two drivers navigate a single-lane road in opposite directions (Fig. 2). Each aims to reach their destination directly, maximizing their benefit b, while steering off the road incurs time loss and costs c, assuming that $b > c$ (Table 1). This interaction creates a situation of "strategic interdependence," where each individual's decision depends on their expectations of the other's actions [95]. If one anticipates the other will swerve, one should proceed straight ($b > b - c$). Conversely, if one expects the other to go straight, one should swerve to avoid a collision ($0 < b - c$). A collision occurs if both hesitate to compromise, leading to the worst outcome.

In a single encounter, there is no definitive solution to the chicken game. Through repeated interactions, drivers are able to develop a cooperative strategy known as "alternating reciprocity," where they take turns giving way. This coordination allows drivers to maximize collective payoffs and share them equitably through repeated interactions [11, 92]. For example, in a two-round interaction, always swerving results in an average payoff of $b - c$, whereas alternating reciprocity yields a higher payoff of $b - c/2$ for each driver (Table 1). Achieving this socially desirable outcome requires at least one person to initially concede without any assurance of reciprocation, setting the stage for mutual cooperation.

Using this interaction setting, we examine the dual effects of realism and shared autonomy on social coordination, specifically the occurrences of conflicts (the worst outcome) and those of alternating reciprocity (the best outcome). Prior work has used this game setting to investigate how autonomous systems and shared autonomy affect social coordination [78, 82, 94, 106, 107]. This study adds the dimension of reality versus virtuality to that work, focusing on the effects of realism, as well as the interaction with shared autonomy, on social coordination. Combining the findings from this study with prior work enables us to provide a comprehensive understanding of how realism and AI assistance interact and influence social coordination.

To examine the effects of realism and AI assistance, it is also important to consider the role of communication in social coordination. When individuals share reciprocity norms, signal exchanges, such as eye contact and hand signals, can activate these norms, facilitating mutual anticipation and self-organization [56, 59, 88]. In real-world environments, such communication can be more effective, as individuals perceive their counterparts as more authentic, enhancing their willingness to exchange intentions. Furthermore, if prosocial norms are stronger in the real world than in the virtual worlds, improving realism may make communication more frequent and impactful, leading to greater reciprocity. Therefore, communication might facilitate reciprocal actions more robustly when people perceive their interactions as occurring in the real world than in the virtual world.

In summary, we address the following research questions in this study:

- RQ1 How does realism affect social coordination and communication effectiveness?
- RQ2 How does AI assistance affect social coordination and communication effectiveness?
- RQ3 How do realism and AI assistance interact to influence social coordination?

4 Methods

4.1 Experiment Setup

To address these research questions, we operationalized the chicken game as a human-subject experiment, manipulating the environment in which their interactions occurred, virtual or real world; in parallel, we also manipulated automation and communication capabilities. Our experiment followed a $2 \times 2 \times 2$ design with three independent variables: "interaction context" (real or virtual environment), "AI assistance" (absence or presence of autosteering assistance), and "communication capability" (absence or presence of a messaging function). This study was preregistered [79, 83] and approved by the corresponding author's institution's committee on the use of human subjects.

We recruited human participants through Amazon Mechanical Turk, selecting only experienced US-based workers to minimize potential variability in driving conventions and streaming latency. Participants join the experiment through their Internet browsers from their residences. After providing consent, they took tutorials, and their comprehension was verified using four multiple-choice questions. Only those who fully understood the game settings — including whether their interaction would be in a virtual or physical space — qualified for the game. This process resulted in 240 qualified participants for the experiment (see Appendix Table A1 for their demographics).

We randomly paired qualified participants and assigned them to one of the two 'cars' (a 'yellow' or a 'blue' car) that existed in a virtual environment or as physical miniature vehicles (see Appendix Section A.1 for details of the apparatus). The participants remotely controlled the assigned cars, where the cars were placed on a single road that led from a starting point directly to a goal area set in a simulated grassland environment (Fig. 2). They experienced the interaction context from a first-person viewpoint using an onboard camera (virtual or real) camera view, controlling the driving speed and whether to drive on or off the road. Driving off the road resulted in a 75% reduction in speed. Before the actual rounds, participants individually practiced two rounds of the game: one without an obstacle and one with an obstacle. Then they were asked to identify the obstacle to confirm their ability to see their camera views on their browsers. Only pairs in which both successfully completed the practice rounds proceeded to the main game.

After the practice rounds, participants played the remote-driving game with the same counterpart over ten rounds. In each round, they received a bonus based on how quickly they reached the goal within the limited time of 30 seconds. The bonus started at US$1.50 and decreased with time; if they did not arrive within 30 seconds for any reason, including a crash, they earned no bonus for that round. As their counterpart drove their car on the same road in the opposite direction, each participant had to decide whether to yield by losing their own time and potential earnings while driving to the goal. This setup operationalized the chicken game's payoff structure, as shown in Table 1, without requiring explicit behavioral choices such as "Go Straight" or "Swerve." Participants were solely incentivized to reach the goal as quickly as possible, with their counterparts driving in the opposite direction.

In addition to the performance-based bonus, participants received US$2.00 upon completing the tutorial (even if they did not qualify for the game) and US$1.50 upon completing all ten rounds of the game and a post-game survey.

4.2 Treatments

Within this basic setup, we manipulated the interaction context by having participants play either in a virtual or real space (Fig. 3A). In the 'virtual' condition, the participants played the game with virtual cars in a three-dimensional virtual space created using the Unity game engine [33]. We intentionally designed the virtual environment with moderate realism to ensure that the participants could clearly distinguish it from the real world. In the "real" condition, participants played (remotely) with palm-sized robot cars in a real diorama space (see Appendix Section A.1 for details). Using this remote-control setup for the real condition, rather than a highly realistic virtual environment, allowed us to avoid any potential deception, such as presenting a virtual environment as real. This

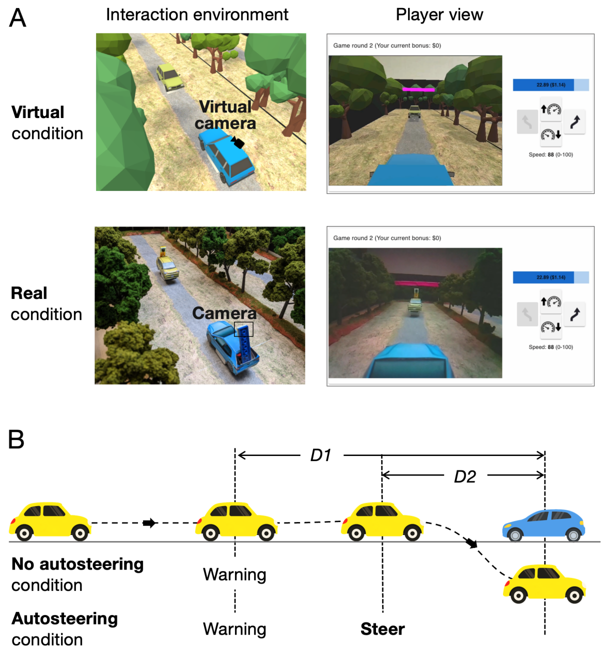

Figure 3: Experimental setup about interaction context (A) and AI assistance (B).

setup also minimized the reliance on the subjective belief of the participants in the authenticity of the environment, which could otherwise be influenced by individual factors.

Regardless of the condition, participants remotely controlled their assigned cars on their Internet browsers from their residence, viewing the environment through an onboard camera mounted on the cars. We maintained consistency across both environments regarding payoff structure, user interface, object configurations, and control systems. We verified that the player's perspective and vehicle motions were nearly identical when applying the same operation data, although context-specific factors like friction and texture persisted (see Supplementary Video). With the qualification process, we ensured that all participants recognized whether they were interacting in a virtual or real space.

Independent of interaction context, we also controlled the car's capacity for AI assistance (Fig. 3B). Following previous work [82], we implemented an emergency safety assistant system in the cars that players drove. In the "no autosteering" condition, participants needed to control their cars all the time. When their cars approached an obstacle, such as their counterpart's car, at a certain distance (about 350 mm between vehicle's centers; *D1* in Fig. 3B), they would receive a warning. In this condition, at least one of the players needed to steer their car to avoid collision on their own. On the other hand, in the "autosteering" condition, participants drove cars equipped with a safety assistance system that automatically steered to avoid obstacles at a minimal distance (about 210 mm between centers; *D2* in Fig. 3B) after a warning. This autosteering feature allowed cars to avoid collisions automatically even when human players did not take evasive action on the main road. Note that autosteering was active only when cars were on the main road (as participants were informed in the tutorial); thus, participants could still collide when they rammed their counterparts from the side.

Furthermore, we implemented a communication system that allows participants to communicate while driving. Half of all the experiment pairs could not communicate with each other during the game. The other half had a messaging function that allowed them to send two fixed-text messages of "Go ahead." and "Thank you!" to their counterpart. Like eye contact and hand signals, these messages could only be received when the sender's vehicle was within the recipient's first-person camera view. These predetermined messages could help players have mutual anticipation in parallel with their actions during (but not before) the game [19, 57, 59].

In summary, we evaluated eight treatment combinations of interaction context (virtual or real), autonomous assistance (presence or absence of an autosteering function), and communication capabilities (presence or absence of a messaging function). Both players in a pair were assigned to the same condition and were aware of this assignment. As preregistered[79, 83], we conducted 15 sessions for each treatment combination for a total of 120 groups (sessions) with 240 participants. Each participant played only one session consisting of 10 rounds of the chicken game.

4.3 Measures

4.3.1 Paired Behavior. We evaluated the treatment effects on paired behavior, especially the occurrences of conflicts and reciprocal actions, with and without communication capabilities. We classified paired behaviors observed per round into four categories: yellow car swerved while blue car went straight (*unilateral* turns by yellow car; Y); blue car swerved while yellow car went straight (*unilateral* turns by blue car; B); both cars swerved (*bilateral* turns); and the cars crashed. This classification was based on the parallel distance and intermediate point between the paired cars when they passed each other (if they did not pass, the behavior was classified as a crash).

Then we identified paired-behavior sequences as reciprocal actions when unilateral turns alternated between participants across rounds. Reciprocal actions followed two basic patterns: Y-B and Y-Y-B-B (or B-Y and B-B-Y-Y). We did not observe any instances of reciprocation that involved more than two consecutive concessions. Thus, some unilateral turns were part of a reciprocal sequence, while others were not (e.g., when one player consistently yielded to the other). At an aggregate level, we evaluated the proportions of unilateral turns within and outside reciprocal sequences, bilateral turns, and crashes (i.e., conflicts) across the different experimental treatments.

4.3.2 Social Value Orientation. To analyze individual decision-making, we measured the driving trajectories of each participant across the rounds, focusing on their behavior passing or colliding with their counterpart. We evaluated these trajectories using the Social Value Orientation (SVO) framework, which assesses actions along axes of self-interest and altruism [60, 78]. Participants displayed a measurable SVO since both their own and their counterparts' payoffs were contingent on their driving behavior when facing each other.

To quantify rewards, we considered each participant's travel distance towards their goal (x_i; indicated by the black and blue dot lines in Fig. 2) and the time (t) taken until they passed or collided with their counterpart. A participant's reward to self in a round was defined as:

$$Reward\ to\ Self_i = x_i/t \tag{1}$$

When a participant i swerved to yield, they allowed their counterpart j to travel further, providing a reward to the other. This reward was defined based on the counterpart's travel distance during the yielding participant's off-road movement ($x_{j,freeway}$; indicated by the blue dot line in Fig. 2), with the reward to other defined as:

$$Reward\ to\ Other_i = (x_{j,freeway} - x_{i,freeway})/t \tag{2}$$

Note that this calculation excluded the instances where participants had activated autosteering assistance, as their swerving lacked intentionality in providing rewards to their counterparts.

We evaluated each behavior's social orientation using the SVO angular phase, defined as:

$$\phi_i = \arctan(Reward\ to\ Other_i/Reward\ to\ Self_i) \tag{3}$$

An SVO angular phase of 0 indicates egocentric behavior, while deviations from 0 suggest more social behavior (positive values indicating prosocial actions, and negative values indicating dependent actions). For instance, alternating turns in giving way results in positive and negative angular phases across the consecutive rounds.

4.3.3 Reciprocity Mechanism. We employed structural equation modeling to analyze the causal paths from technical factors to the attainment of reciprocal actions, mediated by changes in driving and communication. This analysis followed a two-step process: first, one player would give way while the other went straight (*pre-reciprocal* unilateral turn); second, the roles would be reversed in the next round (*reciprocal* unilateral turn). Thus, reciprocal turns were contingent on unilateral turns in the previous rounds. We conducted two path analyses: one using all data except for reciprocal unilateral turns and the other focusing solely on data with unilateral turns.

Before performing the path analysis, we verified that first-order Markov chains [53] adequately modeled the transitions of the paired behavioral states in our experiments. This implies that each subsequent paired behavioral state primarily depends on the immediately preceding one, allowing us to concentrate on the most recent states to estimate the state transitions. For model development, we started with complex models and systematically removed insignificant variables adhering to the principle of Occam's razor [7]. As a result, the models retained only statistically significant variables with 95% confidence intervals.

4.3.4 Overall Performance and Experience. Finally, we evaluated participants' total earnings and satisfaction as indicators of overall performance and experience. Participants earned monetary stakes every round in proportion to the time taken to reach the goal. If they failed to reach the goal within 30 seconds for any reason, including collisions, they received no earnings for that round. Therefore, the total earnings accumulated by participants reflect their objective performance in the coordination scenario.

In addition to objective measures, we evaluated participants' subjective satisfaction with their coordination experience through a post-game survey. Participants rated their satisfaction with themselves, their counterparts, and their cars using a 5-point Likert-type scale, with scores ranging from -2 (very dissatisfied) to 2 (very satisfied). We used linear regression models to analyze the impact of the experimental treatments on both total rewards and satisfaction scores. We supplemented the statistical results with a qualitative analysis of participants' open-ended comments on their behavior in the post-game survey.

5 Results

5.1 Effects on Social Coordination

We found that enhancing realism contributed to a reduction in collisions — the worst outcome of social coordination — especially in the absence of autosteering assistance (Fig. 4). Without autosteering assistance, collisions occurred at a rate of 18.7% in the virtual environment, decreasing to 11.3% in the real environment without the messaging function. When the messaging function was enabled, these rates were 22.7% in the virtual environment compared to 10.7% in the real environment. However, when autosteering assistance was introduced, collision rates dropped harshly, resulting in no meaningful differences due to realism.

Realism also influenced reciprocal actions — the best outcome of social coordination — but the direction of the effect varied depending on communication capabilities (Fig. 4). Without the messaging function, people took turns giving way at a rate of 15.3% in the virtual environment, which dropped to 4.7% in the real environment. In contrast, with the messaging function being enabled, these rates increased to 17.3% in the virtual environment and further to 24.7% in the real environment. Similar to the effects on collisions, the differences in reciprocal actions due to realism disappeared when autosteering assistance was introduced. Consistent with previous work [82], auto-steering assistance strongly suppressed the emergence of reciprocity, and participants never reciprocated under any combination of interaction context and communication capabilities.

We verified these findings through statistical analysis using a penalized multinomial logistic regression model (Fig. 5; see Appendix Table A2 for details). The Firth penalization method was employed due to the absence of data in certain treatment combinations (e.g., unilateral turn within reciprocal actions in the sessions with autosteering assistance; Fig. 4B), which standard logistic regression cannot handle due to the complete separation of variables [50]. The analysis confirms that realism significantly reduces collisions (p = 0.002) and also reciprocal actions ($p < 0.001$). The model coefficients suggest that autosteering assistance has an even stronger negative effect on both collisions and reciprocity ($p < 0.001$; Fig. 5). Communication capability marginally facilitates reciprocal actions ($p = 0.050$) while slightly increasing collisions ($p = 0.022$). The only significant interaction effect observed is between perceived real-world context and communication capability on the emergence of reciprocity. Realism enhances the positive effect of communication on reciprocal actions ($p = 0.017$). Autosteering assistance consistently acted as a strong suppressor of both collisions and reciprocity, regardless of interaction context and communication capabilities.

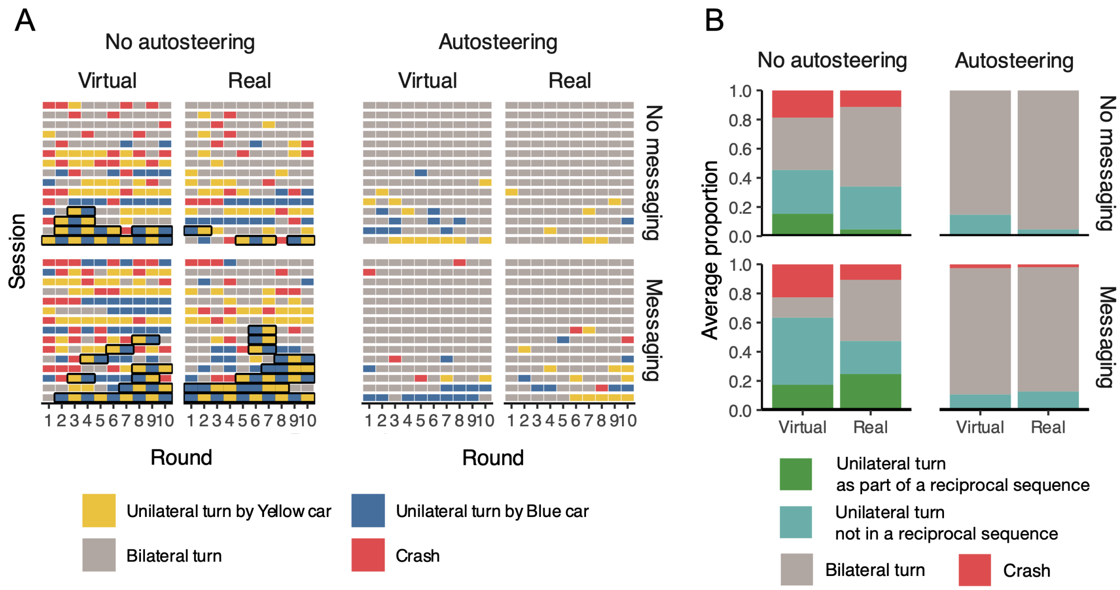

Figure 4: Paired behavior across the conditions. (A) Each row shows a sequence of paired behaviors per session in eight treatment conditions. The bold outline indicates the rounds in a reciprocal sequence. (B) The average proportion of paired behaviors across the conditions (15 groups x 10 rounds for each condition).

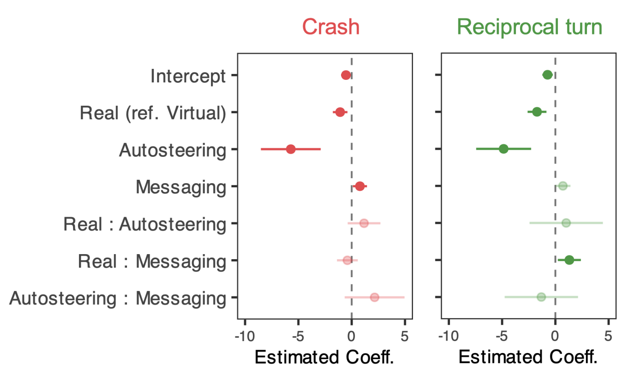

Figure 5: Effects on crash and reciprocal turn. The coefficients are estimated by a penalized multinomial logistic regression model using bilateral turns as the reference category. Error bars are 95% confidence intervals. Dark-color plots for significant coefficients with 95% confidential intervals.

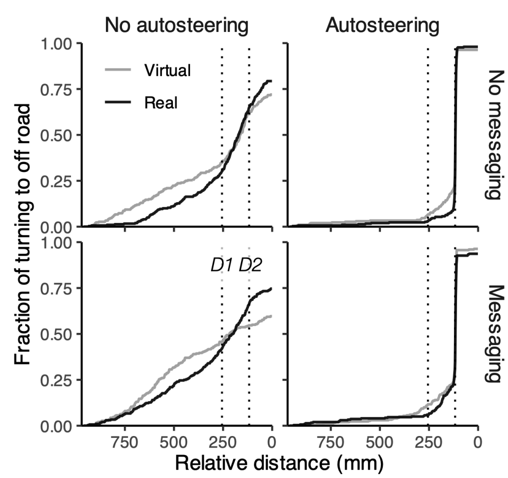

Figure 6: Differences in swerving decision-making across treatments.

5.2 Changes in Individual Decision-Making

We then examined how realism and AI assistance influence individual decision-making. According to Coleman's micro-macro theory [17], extrinsic technical factors, such as interaction modality and AI assistance, do not directly cause the coordination process but instead influence individuals' driving decisions, which lead to collective outcomes such as collisions and reciprocal turns.

Our analysis of driving trajectories revealed that individuals' decision-making regarding swerving varied across the experimental treatments (Fig. 6). Among these treatments, autosteering assistance had the most substantial impact, significantly delaying swerving decisions. Without autosteering assistance, participants swerved and gave way to their counterparts 37.9% of the time before the warning distance (*D1* in Fig. 6) and 61.3% before the distance at which autosteering assistance would be activated (*D2*). These percentages significantly dropped with autosteering assistance to

6.6% at *D1* and 23.5% at *D2* ($p < 0.001$ for both comparisons; test of equal proportions).

The real-virtual context also influenced individuals' driving behavior, particularly in the absence of autosteering assistance (Fig. 6). In sessions without autosteering assistance, realism significantly delayed participants' swerving decisions, resulting in closer distances between vehicles on the road.

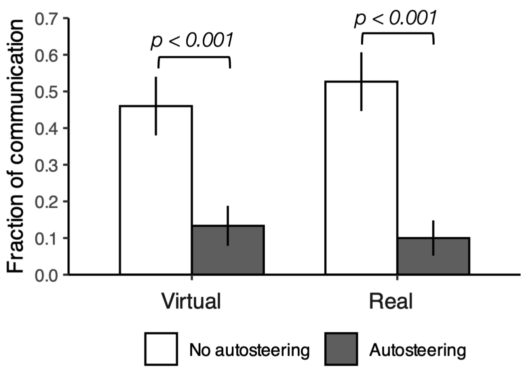

Figure 7: Differences in communciation across treatments.

We also examined how often participants communicated (i.e., one sent at least one message, and the other received it before passing over or colliding) in sessions with the messaging function (Fig. 7). The result showed that autosteering assistance significantly reduced communication ($p < 0.001$ for both real and virtual conditions; test of equal proportions). Conversely, the difference in communication realization between the virtual and real conditions was insignificant ($p = 0.299$ without autosteering and $p = 0.472$ with autosteering; test of equal proportions).

5.3 Changes in Social Value Orientation

Following previous research [78, 82, 94], we applied the Social Value Orientation (SVO) framework to the driving trajectories of participants to evaluate them along the axes of self-interest and altruism (Fig. 8A). In this framework, SVO is represented as an angular preference ϕ that relates to how individuals weigh rewards between themselves and an alter in a coordination setting [60]. Consistent with previous empirical findings on driving coordination [78, 94], the behaviors of the participants were classified according to various social preferences in the absence of autosteering assistance. The angular phases of the SVO was the most distributed in the real environment where participants could communicate (Fig. 8B).

However, when autosteering assistance was introduced, the diversity in social value orientations converged towards self-centered behaviors [82] (Fig. 8). Without autosteering assistance, participants exhibited purely self-interested behavior (i.e., $-2.5° < \phi < 2.5°$) 19.4% of the time. In contrast, this increased to 66.6% of the time with autosteering assistance (rising from 26.3% to 63.6% without messaging and from 18.7% to 65.3% with messaging in the virtual condition; from 14.3% to 81.3% without messaging and from 18.5% to 56.0% with messaging in the real condition). The introduction of autosteering assistance shifted at least 47.2% of people's social value orientation towards self-interest maximization. We confirmed these observations with a nested linear regression model on the absolute SVO angular phases (Appendix Table A3).

5.4 Causal Paths to Reciprocity Process

We examine how realism and AI assistance influence the attainment of reciprocal turns through changes in individual behavior (Fig. 9). Achieving reciprocal turns requires two steps: first, one player would give way while the other went straight (*pre-reciprocal* unilateral turn); second, the roles would be reversed in the next round (*reciprocal* unilateral turn). Thus, we conducted two path analyses: one using all data except for reciprocal unilateral turns to examine the pre-reciprocal step (Fig. 9A) and the other using only data with unilateral turns to examine the reciprocal step (Fig. 9B).

First, we found that realism and autosteering had no direct significant effects on the reciprocity process. This suggests that the effects of these technical factors, as shown in Figs. 4 and 5, are entirely mediated by individual behavioral changes in driving and communication.

Second, participants were more likely to initiate a unilateral turn when one swerved at a greater distance from the other (Fig. 9A). The subsequent player needs enough time to recognize their counterpart's concession and proceed straight. As shown in Fig. 6A, awareness of real-world interactions, as well as autosteering assistance, caused individuals to delay their decisions, suppressing the occurrence of unilateral turns (Fig. 4 and 5). In contrast, communication capacity increased the distance at which participants decide to swerve (Fig. 6A), aiding in the coordination and execution of unilateral turns, which helps coordinate and execute unilateral turns effectively.

Third, the second reciprocal step was influenced by communication in addition to swerving distance (Fig. 9B). When participants communicated, they were more likely to take turns giving way. Moreover, participants communicated more in the real environment than in the virtual environment, particularly after making a unilateral turn in the previous round. On the other hand, autosteering assistance reduced communication, regardless of the interaction context (Fig. 6B). The AI system hindered the emergence of reciprocity in both steps by discouraging people from concession and communication, regardless of how realistic their interaction context is.

5.5 Effects on Overall Performance and Experience

Finally, we evaluated the total earnings and satisfaction of the participants as indicators of their overall performance and experience in social coordination. Figure 10 presents the effects of the experimental treatments on the total earnings of the participants (see the Appendix Table A4 for the detailed statistical result). Our analysis revealed that both the real environment and autosteering assistance significantly improved participants' earnings ($p = 0.007$ for the real environment; $p = 0.001$ for autosteering assistance). Since total earnings were linearly associated with goal completion times, these findings demonstrate that both factors equally enhanced individual performance in the coordination task, albeit through different effects on pair behavior.

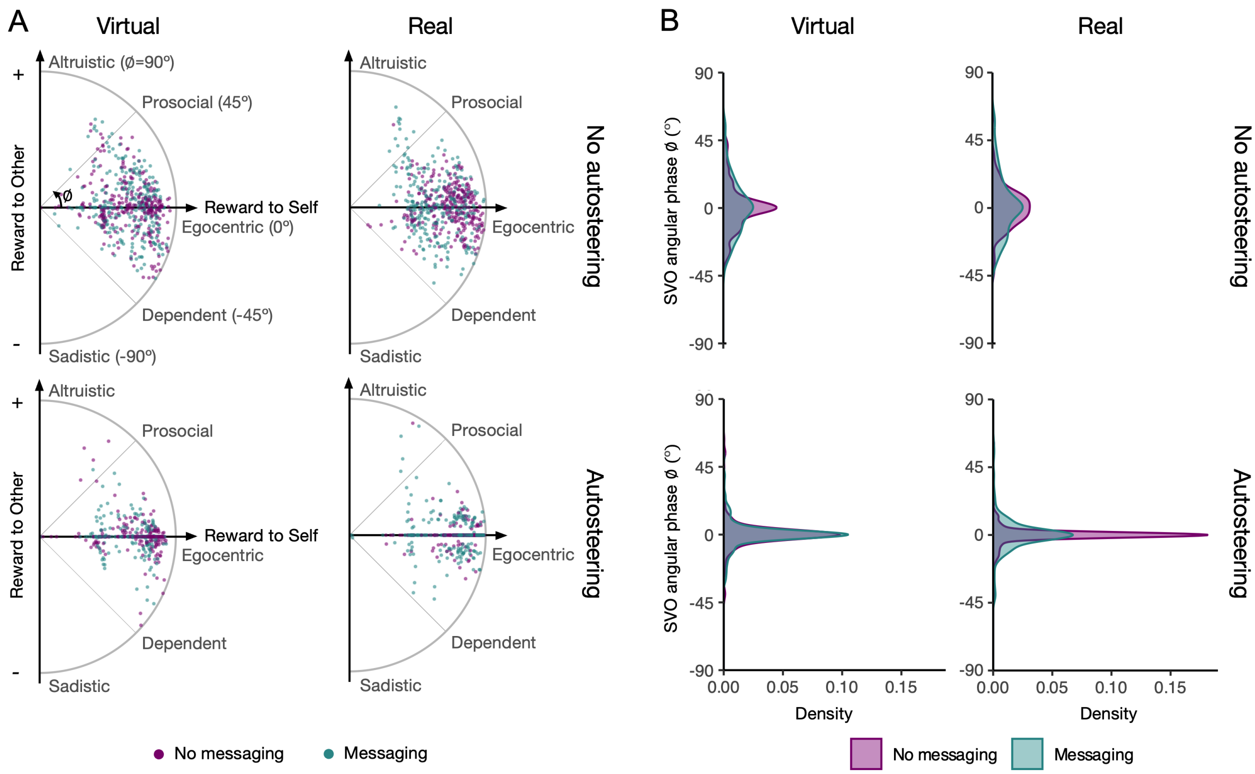

Figure 8: Player's Social Value Orientation per round across the conditions. (A) N=300 for each condition (30 individuals x 10 rounds). The angular phase ϕ represents how individuals weigh rewards between self and others (-90° indicates purely sadistic, -45° indicates dependent, 0° indicates purely egocentric, 45° indicates prosocial, and 90° indicates purely altruistic behavior). In the presence of autosteering assistance, many data points are on the x-axis of "reward to self." (B) clarifies this point using the kernel density estimates of the angular phases.

We also analyzed how real context and autosteering assistance influenced subjective satisfaction and experience (Appendix Table A5). We found that while the driving assistance system enhanced the vehicle's capability, it influenced the driver's self-evaluation (p = 0.010) more than their assessment of the vehicle (p = 0.055). This observation aligns with the SVO result that shared autonomy shifts users' focus toward their performance (Fig. 8). Participants in the autosteering condition often expressed this self-focused attitude in their comments, such as:

P11 "I tried to go as fast as I could and let the autosteering move me out of the way of any obstacles, then tried to get back on the road as quickly as possible. The main goal was to earn as much as a bonus as I could and I wasn't really concerned about the other driver or how they performed."

P12 "I tried to accelerate as fast as possible and chose the maximum speed available. I let the autosteering system choose when to avoid the other vehicle. I trusted that it would choose the optimal time to steer right. I then tried to steer back left onto the road as fast as I could."

P13 "I knew that the automatic steering would save me, so I just tried to accelerate to the limit and turn back onto the road as quickly as I could. The most important thing was to accelerate to the limit."

P14 "I let the automatic steering take over to avoid the other car and then figured out I could swerve back to the left to increase my speed again. I did this because I was trying to figure out to increase my speed and increase my time getting to the finish."

We also found that realism significantly enhanced participants' satisfaction with their cars when they could use the messaging function (p = 0.011). This finding underscores a marked contrast in attitudes under AI-assisted control. In the absence of autosteering assistance, participants in the reality condition demonstrated care for their counterparts through communication, often referring to themselves as part of a team and using phrases like "we" in their comments. Examples of their remarks include:

P21 "I tried to be courteous and let the other driver go ahead. We ended up alternating. I treated the game as I would in a real life situation. I am courteous in real life."

P22 "I tried to trade off "go aheads" with the other driver so as to maximize both our bonuses. The other driver seemed to appreciate this later in the game."

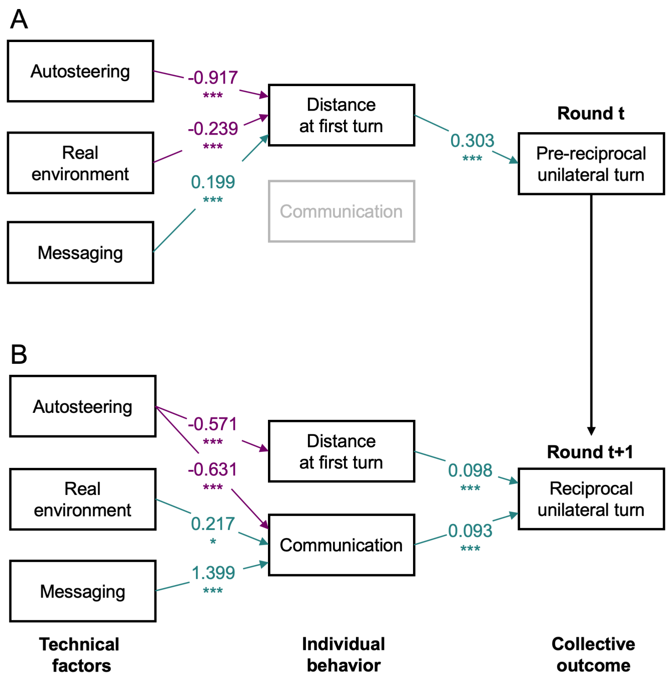

Figure 9: Path graphs of structural equation modeling for reciprocal coordination. Paired players need two-step coordination to establish alternating reciprocity. The first analysis (A) uses all the data except for that having reciprocal unilateral turns (*N*=1107), and the second analysis (B) uses only the data having unilateral turns (*N*=349). All the paths and error variances are statistically significant (*** $p < 0.001$; * $p < 0.05$). The intervening variables are normalized for comparison.

P23 "I tried to establish a pattern of cooperation. I tried to signal my intentions. I thought if we both took turns on the straight path, it would be best for us both. I was a little frustrated from the lack of communication from my partner but I tried to stick to the plan."

P24 "I tried to switch off getting off the road so we could both benefit. I was not always successful and that strategy kind of fell apart after a while. We both turned off mostly."

P25 "We took turns staying on the road."

6 Discussion

We examined the dual effects of realism and AI assistance on social coordination by comparing participants' behavior in a real-world version of the chicken game with its virtual-world counterpart. In this section, we discuss our findings in relation to the research questions, synthesize these insights into a design matrix to outline practical implications, and consider the caveats and limitations of our approach.

6.1 Addressing the Research Questions

RQ1: How Does Realism Affect Social Coordination and Communication Effectiveness? Our findings reveal that realism has a nuanced impact on social coordination. In our experiment, participants did not directly observe the real or virtual environment; instead, they interacted remotely through first-person camera views displayed in their browsers (Fig. 3A). Our comprehension assessment confirmed that all participants accurately understood whether they were interacting in a real or virtual environment (with no deception involved). Moreover, we ensured that the first-person views and movements in the virtual condition mirrored those in the real condition (Supplementary Video). Thus, from the perspective of the participants, the only difference between the real and virtual conditions was their *perception of interacting in the real versus virtual world*. This perception significantly influenced social coordination and communication effectiveness.

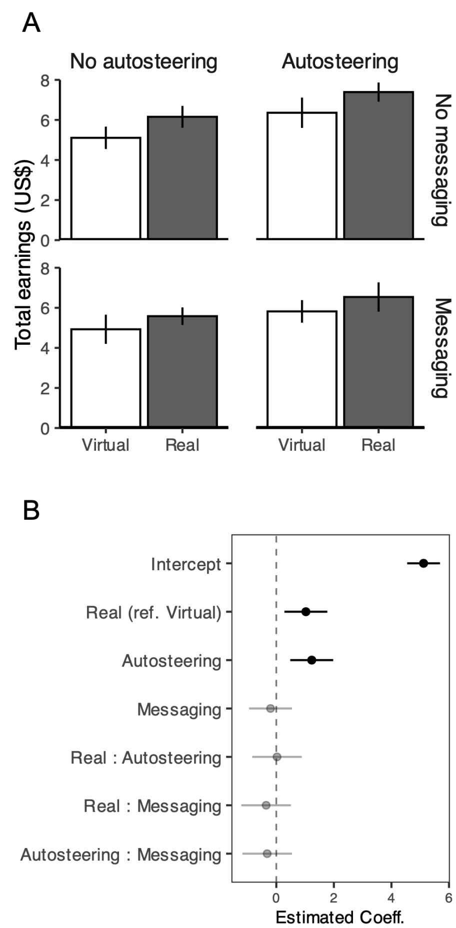

Figure 10: (A) Player's total earnings across conditions (*N* = 30 for each condition). (B) The coefficients are estimated by a linear regression on total earnings. Error bars are 95% confidence intervals. Dark-color plots for significant coefficients with 95% confidential intervals.

In the absence of autosteering assistance, participants in the real condition experienced fewer collisions (i.e., a lower risk of collisions) compared to those in the virtual condition (despite the increased control noise arising from physical friction). They also performed fewer unilateral turns under the real condition when communication was unavailable (Figs. 4 and 5). Participants appeared more cautious in the virtual environment, where crashes were more likely. Enhancing realism might alleviate such concerns [12, 70], but paradoxically it could also lead to delayed swerving (Fig. 6), potentially reducing the number of reciprocal turns within pairs.

Communication capability alone marginally increased reciprocal turns but also led to more conflicts (Fig. 5). The ability to exchange messages allowed participants to establish a shared understanding and anticipate each other's moves, leading to smoother and more cooperative interactions [51, 82]. In our experiment, some participants actually used the communication channel for coordination, but not all did so well (Fig. 7). As a result, successful message exchanges facilitated reciprocal turns, but miscommunication or lack of coordination often increased conflicts.

When communication capability was combined with real-world contexts, however, it significantly improved coordination and facilitated reciprocity (Figs. 4 and 5). Participants in the real condition were more inclined to communicate their concessions than those in the virtual condition (Fig. 9), leveraging participants' perception of real-world interactions to coordinate effectively and reduce collisions. These findings suggest that the realism of interaction contexts, as perceived by humans, can enhance the authenticity of interaction partners, thereby encouraging reciprocal behaviors through improved communication.

RQ2: How Does AI Assistance Affect Social Coordination and Communication Effectiveness? In our experiment, autosteering significantly reduces the incidence of reciprocal actions as well as collisions (Fig. 4). In the default setting of the chicken game, each party's best outcome depends on their counterpart's choice (Table 1). If one swerves, it is optimal for the other to go straight and vice versa. If both wait to see what the other does first, they risk colliding, which is the worst outcome. However, when autosteering assistance is introduced, the interaction structure is transformed, and the strategic interdependence is dissolved [82]. Since the AI assistance system autonomously manages collision risks, individuals can maximize their rewards by going straight, regardless of their counterpart's choice. Thus, it diminishes the need for communication and reciprocal behavior. Instead, it encourages users to focus on self-interest (Fig. 8), leading to aggressive driving behaviors.

RQ3: How Do Realism and AI Assistance Interact to Influence Social Coordination? Although we did not observe significant interaction effects between realism and AI assistance (Fig. 5), this absence itself highlights an important insight: the influence of AI assistance is so dominant that it overrides the effects of realism. Autosteering assistance had a strong suppressive effect on the emergence of reciprocity, regardless of whether the interaction occurred in a real or virtual environment (Fig. 4). The AI assistance reduced participants' need to engage in reciprocal behavior, as the system autonomously handled critical aspects of collision avoidance. This reliance on AI assistance consistently suppressed reciprocity across both real and virtual contexts. These findings suggest that while realism alone can influence reciprocal behaviors, the introduction of AI assistance fundamentally can alter the dynamics of social coordination by eliminating the necessity for communication and mutual anticipation. In addition, AI assistance does not "perceive" the reality of interaction contexts as humans do. Thus, when people incorporate AI assistance into their decision-making, the effects of realism are inevitably limited in the process.

Both realism and AI assistance were found to improve behavioral performance (Fig. 10). Both factors reduce collisions and improve safety, leading to an overall improvement in performance (Fig. 5). However, *the mechanisms behind these improvements fundamentally differ*. In the real-world context, participants communicated more frequently, fostering reciprocal actions (Fig. 9). This collaborative dynamic led to more efficient use of the shared space, improving collective performance. In contrast, autosteering assistance suppressed reciprocity but allowed participants to drive faster and minimize time loss by swerving (Fig. 6). Although this approach prioritized individual gains over collaboration, it still contributed to overall performance improvement by reducing collision risks.

These differences are also reflected in participants' subjective evaluations of their experiences (Table A5). Participants reported greater self-satisfaction when using autosteering assistance, likely due to AI assistance enhancing their confidence and perceived task success. On the other hand, when realism was combined with communication, participants expressed greater satisfaction with their vehicles. This finding suggests that realism can improve the perceived authenticity of interaction partners, amplifying the benefits of communication. In turn, this improved coordination experience made vehicle-mediated interactions more rewarding. This interaction effect was further evidenced by the emergence of reciprocity (Fig. 5) and the SVO analysis (Table A3), demonstrating that realism and communication can synergize to create a more positive user experience.

6.2 Implications for Design

Based on our findings, we propose a design dimension that illustrates how realism and AI assistance influence key factors for social coordination, such as interpersonal interdependence, reciprocity, and private gain (Fig. 11). Our controlled experiment simulated social situations in which individual interests conflict (i.e., strategic interdependence), requiring social coordination. This design dimension extends beyond the specific context of our study and serves as a guide for creating diverse social interaction systems. In this section, we explore the design implications of this dimension and discuss potential application scenarios.

6.2.1 Divergent Impacts of Realism and AI Assistance. As we described in Section 6.1, realism and AI assistance create distinct experiences, each addressing the strategic interdependence of social coordination through different mechanisms (Fig. 11). Increasing realism (i.e., transitioning from virtual to realistic contexts) combined with communication addresses coordination challenges by enhancing the perception of partner authenticity and activating interpersonal cues, which promotes reciprocity. However, this cooperative behavior often incurs coordination costs for individuals, such as slower behavioral responses and the potential for miscommunication. In contrast, AI assistance decouples the strategic interdependence of social coordination by eliminating concerns about interpersonal conflicts. This enables individuals to focus on their personal goals, enhancing their egocentric experience. Understanding the two pathways to addressing coordination challenges

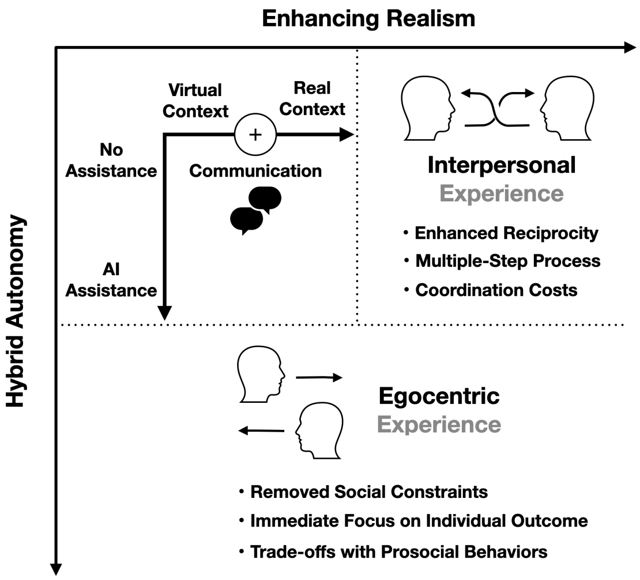

Figure 11: Design dimension across realism and hybrid autonomy. Realism combined with communication fosters interpersonal experiences, characterized by enhanced reciprocity, multiple-step coordination processes, and coordination costs. In contrast, AI assistance shifts user experience toward an egocentric focus, removing social constraints, emphasizing individual outcomes, and creating trade-offs with prosocial behaviors. When both factors are present, the egocentric effects of AI assistance overshadow the interpersonal benefits of realism.

is crucial for system design. Practitioners developing coordination systems should carefully evaluate which aspects to prioritize — whether to foster interpersonal experiences through collaborative activities or to minimize social constraints to enhance individual performance.

6.2.2 Realism Promotes Interpersonal Experience. When designing coordination systems to foster interpersonal experiences through collaborative activities, leveraging real-world contexts is a valuable option but should be complemented by robust communication capabilities (Fig. 11). Our SVO analysis (see Section 5.3) revealed that social coordination improves, and altruistic behavior emerges in real-world contexts, but only when communication is available. In contrast, the absence of communication in real-world settings can suppress reciprocal behavior. While realism can amplify the effectiveness of communication in fostering reciprocity, it can also exacerbate coordination challenges when communication is absent. This is because social coordination requires mutual understanding, often established through a multi-step process.

As discussed in Section 5.4, establishing reciprocal behavior involves a two-step process that relies on achieving mutual understanding within the study setting. Similarly, designing coordination systems to enhance interpersonal experiences should be approached with careful attention to ensure that users can effectively navigate multiple coordination processes. These findings underscore the importance of complementing realistic environments with robust communication functionalities. For example, in an online virtual meeting application, realism can be enhanced through realistic avatars, spatial audio, and environmental cues. These features help align user communication with real-world social norms, fostering smoother and more cooperative interactions. In digital workspaces, incorporating designated messaging features that promote reciprocal social norms can also be effective, even when implemented as small, preformatted cues — such as the "thank you" and "go ahead" functions used in our experiment [40].

6.2.3 AI Assistance Leads to Egocentric Experience. When individual productivity is the primary focus in tasks requiring social coordination, implementing AI assistance that overrides user decision-making can enhance performance by reducing the need for interaction. Introducing strong automation, where AI overrides critical human decisions, shifts the user experience toward an egocentric focus (Fig. 8 and Table A3). By eliminating the need to account for conflicts with counterparts, users can concentrate solely on maximizing their individual benefits (Fig. 11). This transition to an egocentric experience induced by AI assistance is consistent across real and virtual interaction contexts.

Our findings suggest that for tasks where rapid task efficiency and individual outcomes are prioritized, such as factory operations, vehicle control in public transportation, or heavy machinery operation, adopting AI assistance can optimize productivity and enhance safety. In these scenarios, system stability and individual performance outweigh the need for interpersonal experience, making strong automation a viable and effective option.

6.2.4 Dominating Influence of Human-AI Hybrid Autonomy. The concept of mixed-initiative [35] has provided an important HCI framework to explore the boundaries between direct human manipulation and the delegation of actions to automated computer agents. With the rapid emergence of AI assistants, these boundaries are undergoing significant transformation. For example, large language models (LLMs) such as ChatGPT have advanced beyond simple text correction to enable the delegation of higher-level decisions. This advancement illustrates how AI can now intervene in domains traditionally governed by human judgment, paving the way for dynamic human-AI collaboration characterized by *hybrid autonomy*.

The potential impact of hybrid autonomy extends beyond automated driving [76, 98] and real-time conversation [43] to include human-robot interaction [4], tele-robotics [21, 104], and human body manipulation through wearable devices [45]. However, the introduction of hybrid autonomy warrants careful consideration. As our study demonstrates, AI assistance does not merely support existing coordination practices; it can fundamentally reshape social dynamics. Specifically, its egocentric effects can overshadow humans' prosocial tendencies rooted in real-world interactions, altering the fundamental nature of social coordination.

In scenarios where AI takes on significant decision-making roles, as observed in our experiments, the focus shifts toward individual outcomes at the expense of reciprocity and interpersonal understanding. While this shift can boost individual convenience and competence, it simultaneously suppresses opportunities for meaningful communication and collaboration with other people — values that remain central to many societal contexts.

The insights gained from our experiments provide critical implications for designing social coordination systems premised on hybrid autonomy. Our proposed design dimension offers actionable guidelines and predictions for future scenarios in which humans and AI operate as hybrid agents. It highlights the importance of balancing egocentric performance enhancements provided by AI with the need to preserve prosocial behaviors enabled by realism and communication. HCI practitioners must carefully consider these dynamics to create systems that optimize individual and collective outcomes effectively.

6.3 Limitations and Future Work

Our study provides insight into the dual effects of realism and shared autonomy on social coordination, but several caveats and limitations should be noted.

For example, we used the chicken game as the model for social coordination. This well-studied and established model captures a critical challenge of social coordination: strategic interdependence [95], where each individual's reward depends on the other's choices, and the potential for indeterminate consequences can lead to the worst outcome [51, 73, 106, 107]. However, real-world social coordination is influenced by additional factors, such as value misalignment, miscommunication, power dynamics, and information asymmetry. We believe that our findings remain relevant to more complex forms of social coordination, but these additional factors may overshadow the effects we observed, much like the way AI assistance dominated the effects of realism in our study.

Another limitation of our study is that the same pairs of participants interacted over multiple rounds in a single-session format. While this design choice enabled consistent comparisons within pairs, it can limit the applicability of our findings to more dynamic HCI contexts, where interactions often involve multiple agents or change participants endlessly. Future studies in multi-agent dynamic settings or real-world interaction scenarios are necessary to validate and extend our results.

Furthermore, we operationalized the chicken game using miniature remote-controlled cars for the real-context condition. This experimental setup allowed us to examine behavioral effects directly, which often differ from attitudinal effects measured through surveys [103]. It also facilitated strict comparisons with virtual interactions, isolating the effects of realism. However, the setup does not encompass the full spectrum of the reality-virtuality continuum [54]. In more immersive settings with advanced user interfaces, such as virtual reality headsets or augmented reality systems [29, 42], or by driving actual cars on real roads, participants could exhibit more cautious behavior due to an increased perceived risk of collisions. Consequently, the baseline behaviors observed in our study could differ under these alternative conditions.

We also examined the effect of AI assistance in a specific form: autosteering assistance. However, different types of AI assistance may influence human decision-making in different ways, thus altering their interaction with realism. For example, previous studies have shown that even in the same interaction scenario, changing speed instead of direction, such as by using autobraking assistance, increased reciprocity rather than suppressed it [82]. Realism might amplify the positive effects of such forms of AI assistance on reciprocal coordination. Furthermore, uncertainty or imperfection in AI system actions can affect user trust in the system, reducing AI adaptation [27]. Exploring other forms of AI assistance across the reality-virtuality continuum will enrich our understanding of how various types of AI assistance interact with realism to shape social coordination dynamics.

Finally, our study sample may not fully represent the diversity of real-world users. Although participants were recruited through Amazon Mechanical Turk, providing a more sociodemographically diverse pool compared to traditional student samples, the sample was still biased toward specific demographic groups (Table A1). Additionally, participants were limited to US residents to minimize potential variability in driving norms and latency issues. However, different demographic groups may exhibit varying customs, values, and norms in communication and social coordination, which could influence the observed effects of realism and AI assistance [2]. Future research should aim to include more geographically and culturally diverse samples to enhance the external validity of this work.

7 Conclusion

In this study, we explored the dual effects of realism and AI assistance on social coordination and reciprocal behaviors using a remote-controlled robot experiment and its virtual counterpart. Our findings reveal that realism can significantly enhance reciprocity through communication in social interactions. In contrast, AI assistance that overrides human decision-making in critical moments shifts users' focus toward self-interest, reducing the need for social coordination and communication. When both factors are present, the suppressive effects of AI assistance dominate, diminishing the positive impact of realism. This indicates that realism alone is insufficient to sustain effective social coordination in highly automated contexts.

These insights provide practical design guidelines for understanding the necessities and limitations of enhancing realism in interactive systems involving AI assistance. Realistic elements can enhance social coordination when combined with communication capabilities, but these effects are most effective when agents who perceive reality (i.e., human users) retain full control over decisions. With recent advances in AI, shared autonomy has emerged, where humans and machines jointly make decisions within a single entity, such as in semi-automated driving and AI copilots for writing and coding. In such settings, addressing potential disengagement caused by AI assistance becomes a crucial design challenge. By thoughtfully integrating advanced virtual reality and automation with opportunities for human intervention and communication, designers can create more effective and engaging HCI applications that support both individual efficiency and collective coordination.

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A Appendix Sections

A.1 Apparatus

A.1.1 Basic Setup. Our experiment was implemented with the Breadboard platform [52]. Participants interacted anonymously over the Internet using customized software accessible via a browser window. The user interface included a view from the onboard camera of their assigned vehicle, control buttons, and indicators displaying the remaining time and current speed.

To minimize confusion during remote operation, vehicles were restricted to three fixed, invisible lanes: one "on-road" lane and two "off-road" lanes (Fig. 2). Participants controlled their vehicles with four options: speed up, speed down, move to the right lane, or move to the left lane. Backward movement was not allowed. Leftward and rightward movements were also constrained to enhance usability. When on the road, participants could move right to avoid an obstacle. Once off the road, they could only move left to return to the main road. This was enforced by activating or deactivating the relevant steering buttons based on the car's position.

At the start of each game round, participants needed to activate their car. Vehicles began at an initial speed of approximately 43 mm/sec, and participants could adjust the speed up to a maximum of 130 mm/sec or reduce it to a complete stop. If the car's speed dropped below the initial speed, it came to a halt. When participants moved from the main road to an off-road lane, the car's speed automatically decreased by 75%, capping the maximum speed at 35.5 mm/sec.

In sessions where participants had access to messaging functionality, two additional buttons were available: "Go ahead" and "Thank you!" When a button was clicked, the corresponding message appeared over the sender's vehicle image in the recipient's camera view. To ensure visibility, the sender needed to be within the range of the receiver's camera for the message to appear.

A.1.2 Real Environment. In the real condition, each remote-controlled vehicle consisted of a standard robot cube (Sony's Toio [87]), a small single-board computer (Raspberry Pi Zero W), and a 120-degree angle camera. It was covered with the paper craft of a yellow or blue car (Fig. 3). The robot vehicle size was about $40 \times 90 \times 65$ mm. The robotic cubes moved at a maximum speed of about 300 mm/sec and recognized their absolute location with an underbody sensor by detecting an invisible ink pattern on specific paper sheets that formed the "ground." This allowed us to control vehicles based on distance (e.g., for active assistance treatments) and location (e.g., for the 75% speed reduction during 'off-road' driving) without relying on algorithmic location estimation. The onboard cameras were used only for participants to see the environment and control their vehicles. They faced in the direction of forward movement to show the front view with the tip of their own vehicle body (Fig. 3), which helped the participants to sense the distance from an oncoming object. The camera view was transmitted to the participants assigned through the Web Real-Time Communication program [46]. We confirmed that the streaming latency was small enough that people could control the remote vehicle with the live view in the experiment environment (around 300 milliseconds within the US and less than 500 milliseconds between the US and Japan).

A.1.3 Virtual Environment. The virtual world was created using Unity 2021.3.26f1, utilizing the Universal Rendering Pipeline (URP) to ensure the computing latency for the game did not affect the latency of the live view. Low polygon models were utilized throughout the game to reduce the computing power and rendering latency. The dimensions and physics of the virtual Toio models utilized the official Unity Toio package [36] to ensure compatibility of the movement of the virtual model to the real model. A virtual camera was set up at the same 120-degree angle as the real-world setup, which followed the car's movement. The camera view was transmitted to the participants using the same Web Real-Time Communication protocol [46] as the real scenario for low latency streaming. Each virtual car was equipped with a physics engine to detect when virtual objects come in contact with each other and to toggle the speed reduction during 'off-road' driving. Signals from the main program calculated the active assistance treatments, position, and direction, allowing for the same game logic to be used as the real-world setup and separation of rendering and logic.

B Appendix Tables

Table A1: Demographics of experiment participants. The data were self-reported by the participants (*N* = 240).

	Characteristics	Count	Percentage
Gender	Female	98	40.8%
	Male	137	57.1%
	Non-binary	2	0.8%
	No answer	3	1.3%
Age	18 - 29	44	18.3%
	30 - 39	86	35.8%
	40 - 49	64	26.7%
	50 - 59	32	13.3%
	$\geq$ 60	13	5.4%
	No answer	1	0.4%
Race / Ethnicity	White, Caucasian, European; not Hispanic	203	84.6%
	Asian / Pacific Islander	14	5.8%
	Black / African American	11	4.6%
	Hispanic / Latino	5	2.1%
	American Indian / Native American	1	0.4%
	Multiple ethnicity	5	2.1%
	No answer	1	0.4%
Education	High school or less	33	13.8%
	Some college (1-3 years)	56	23.3%
	Bachelor's degree	126	52.5%
	Graduate degree	21	8.8%
	No answer	4	1.7%
Annual incomes, US$	0 - 20,000	50	20.8%
	20,000 - 34,999	48	20.0%
	35,000 - 49,000	49	20.4%
	50,000 - 74,999	50	20.8%
	75,000 - 99,999	29	12.1%
	$\geq$ 100,000	11	4.6%
	No answer	3	1.3%

Table A2: Results of the statistical analysis regarding treatment effects on the fraction of paired-behavior categories. They are estimated by a penalized multinomial logistic regression model using bilateral turns as the reference category. * indicates $p <$ 0.001; ** indicates $p <$ 0.01; * indicates $p <$ 0.05.**

		Coeff.	P value	
Crash	Intercept	-0.536	0.022	*
	Real (ref. Virtual)	-1.083	0.002	**
	Autosteering	-5.711	0.000	***
	Messaging	0.772	0.022	*
	Real : Autosteering	1.160	0.139	
	Real : Messaging	-0.405	0.415	
	Autosteering : Messaging	2.150	0.133	
Unilateral turn not in a reciprocal sequence	Intercept	-0.053	0.783	
	Real (ref. Virtual)	-0.880	0.001	**
	Autosteering	-2.145	0.000	***
	Messaging	0.795	0.004	**
	Real : Autosteering	0.634	0.062	
	Real : Messaging	-0.326	0.321	
	Autosteering : Messaging	-0.424	0.211	
Unilateral turn as part of a reciprocal sequence (Reciprocal turn)	Intercept	-0.732	0.003	**
	Real (ref. Virtual)	-1.723	0.000	***
	Autosteering	-4.856	0.000	***
	Messaging	0.708	0.050	*
	Real : Autosteering	1.017	0.562	
	Real : Messaging	1.314	0.017	*
	Autosteering : Messaging	-1.317	0.453	
Number of observations		1200		

Table A3: Results of the statistical analysis regarding treatment effects on absolute SVO angular phases $|\phi|$. They are estimated by a linear mixed model incorporating random effects for participants. * indicates $p < 0.001$; ** indicates $p < 0.01$; * indicates $p < 0.05$.**

	Coeff.	P value	
Intercept	11.803	0.000	***
Real (ref. Virtual)	-1.588	0.226	
Autosteering	-7.991	0.000	***
Messaging	2.327	0.076	
Real : Autosteering	0.036	0.981	
Real : Messaging	3.094	0.042	*
Autosteering : Messaging	-1.672	0.269	
Number of observations	2400		
Number of participants	240		

Table A4: Results of the statistical analysis regarding treatment effects on participants' total earnings (US\$). They are estimated by a linear regression model. * indicates $p < 0.001$; ** indicates $p < 0.01$; * indicates $p < 0.05$.**

	Coeff.	P value	
Intercept	5.117	0.000	***
Real (ref. Virtual)	1.028	0.007	**
Autosteering	1.231	0.001	**
Messaging	-0.200	0.599	
Real : Autosteering	0.025	0.955	
Real : Messaging	-0.353	0.422	
Autosteering : Messaging	-0.317	0.471	
Number of observations	240		

Table A5: Results of the statistical analysis regarding the treatment effects on participants' satisfaction with themselves, their counterparts, and their cars. They are estimated by linear regression models. * indicates $p < 0.001$; ** indicates $p < 0.01$; * indicates $p < 0.05$.**

	Satisfaction with themselves			Satisfaction with their counterparts			Satisfaction with their cars		
	Coeff.	P value		Coeff.	P value		Coeff.	P value	
Intercept	0.696	0.000	***	0.683	0.000	***	0.750	0.000	***
Real (ref. Virtual)	0.075	0.719		0.033	0.879		-0.233	0.300	
Autosteering	0.542	0.010	**	0.400	0.069		0.433	0.055	
Messaging	0.142	0.497		0.067	0.761		-0.133	0.553	
Real : Autosteering	-0.217	0.369		-0.233	0.358		-0.167	0.521	
Real : Messaging	-0.083	0.729		0.200	0.430		0.667	0.011	*
Autosteering : Messaging	-0.317	0.189		-0.133	0.599		-0.200	0.441	
Number of observations	240			240			240		