Understanding Human-machine Cooperation in Game-theoretical Driving Scenarios amid Mixed Traffic

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ABSTRACT

Introducing automated vehicles (AVs) on roads may challenge established norms as drivers of human-driven vehicles (HVs) interact with AVs. Our study explored drivers' decisions in game-theoretical scenarios amid mixed traffic using an online survey study. We manipulated factors including interaction types (HV-HV vs. HV-AV), scenario types (chicken game vs. public goods game), vehicle driving styles (aggressive vs. conservative), and time constraints (high vs. low). The quantitative results showed that human drivers tended to "defect" more, that is, not cooperate, against vehicles with conservative driving styles. The effect of vehicle driving styles was pronounced when interacting with AVs and in chicken game scenarios. Drivers exhibited more "defection" in public goods game scenarios and the effect of scenario types was weakened under high time constraints. Only drivers with moderate driving styles "defected" more in HV-AV interaction. Our qualitative findings provide essential insights into how drivers perceived conditions and formulated strategies for decision-making.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

automated vehicles; mixed-traffic environment; human-machine cooperation; game theory

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1 INTRODUCTION

With the maturity of automated driving technology and the proliferation of automated vehicles (AVs), the future of transportation will involve a combination of AVs, conventional human-driven vehicles (HVs), and other road users (e.g., pedestrians and cyclists). In mixed-traffic environments, HVs have to frequently interact with AVs. Human drivers mostly navigate driving scenarios without incidents through social norms and signaling [42]. However, introducing AVs on public roads may challenge established norms as HVs learn to interact with AVs. How will human drivers behave as HVs interact with AVs in mixed-traffic scenarios? Will HVs become more cooperative through trust in rule-following AVs? Or will HVs take advantage of AVs for their personal benefit thus decreasing cooperation even with other AVs?

Existing studies have explored the interaction between drivers in HVs and AVs in mixed-traffic environments. Research showed that human behaviors and decisions in HVs were influenced by different factors, such as interaction types (HV-HV vs. HV-AV) [13, 25, 27, 30, 31, 40, 41, 59] and driver driving styles [30]. Evidence [27, 30] suggests that human drivers may have intentions to bully AVs rather than HVs. However, there are some research gaps that need to be addressed. First, AVs have been assumed to be conservative without the possibility for AVs to adapt their behavior based on interactions with other vehicles. The research in HV-AV interaction lacks insights into how the variable, AV driving style, impacts human decision-making, and vice versa. Second, although studies have included multiple driving scenarios, none of them theoretically categorize driving scenarios and investigate their effects on drivers' decision-making in mixed-traffic environments. Insights here may connect directly to a wealth of game theoretic research with the potential to influence policy making while optimizing transportation safety and efficiency. Third, existing literature focuses mostly on one or two variables at a time. However, variables may interact to reveal higher-order outcomes in driving scenarios. Fourth, most prior research on human driver behavior patterns relied on quantitative analyses, without an understanding of how individuals integrate various factors and develop strategies for decision-making. In this study, we fill the research gap by answering the following three research questions:

RQ1: Does the driving style of the interacting vehicle influence human drivers' decisions when they interact with AVs and HVs?

RQ2: How do human drivers' decisions vary across different types of game-theoretical driving scenarios?

RQ3: What information do drivers extract in a given scenario to inform their decision-making process, and what strategies do they employ in making decisions?

To answer these research questions, we developed an online survey study (N=674) to examine drivers' decision-making in different conditions. This study investigated how the interaction types, scenario types, vehicle driving styles, time constraints, and driver driving styles influenced drivers' decision-making in mixed-traffic environments. We identified two types of interaction in mixed-traffic environments: HV-AV and HV-HV, and assumed that all the interacting vehicles had two distinctly different driving styles: aggressive and conservative. Driving scenarios were developed based on game theoretic interactions and time constraints could serve as a factor in manipulating changes in task payoffs.

This study contributes to building an understanding of how human drivers make decisions in a mixed-traffic environment. We delve into human drivers' decisions between cooperation and defection under a systematic game-theoretic framework. Leveraging a mixed-method approach, we illuminate the underlying motivations and strategies that drivers employed during decision-making. This study fills the research gap by emphasizing the pivotal influence of driving styles, both for AVs and HVs, across various game-theoretical driving scenarios. Our findings will provide insights into refining the design and program implementation of AVs, particularly in striking a balance in driving styles to adapt to human behaviors. Future driver behavior prediction and decision assistant systems and vehicle communication systems should take human factors into full consideration to ensure AVs and HVs understand each other's needs, foster collaboration and achieve respective goals in mixed traffic. This may better support a safe, reliable, and effective HV-AV interaction in mixed-traffic environments.

2 RELATED WORK

2.1 Decision-Making in Mixed Traffic

Human behaviors and decision-making in mixed-traffic environments have been widely studied, including the interaction between pedestrians and AVs and between drivers in HVs and AVs. Research on pedestrian-AV interaction showed that pedestrians' crossing behaviors were influenced by AV driving behaviors [19, 39, 65], communication methods [1, 6, 48, 60], road conditions [19], and individuals' characteristics [1, 10, 36]. For example, Colley et al. [6] found that AV external communication, other pedestrians' behavior, and previous experience influenced pedestrians' crossing decisions. Zhao et al. [65] found that pedestrians showed a greater intention to engage in risky road-crossing behaviors in front of AVs compared to HVs. For HV-AV interaction, prior work has shown that interaction types (HV-HV vs. HV-AV) [13, 25, 27, 30, 31, 40, 41, 59], communication methods [7, 45], driver driving styles [30], time constraints [59], and expectations for AVs [33] influenced human drivers' behaviors and decision-making.

Some studies investigated the effect of interaction types on the decision-making of human drivers through web-based surveys [27, 30], driving simulator studies [13, 25, 40, 51, 59], and field experiments [31, 41]. For example, a cross-national survey study [27] indicated that human drivers were more inclined to bully AVs than HVs. Ma and Zhang [30] explored how interaction types and driver driving styles influenced human decision-making and subjective feelings. The results suggested that aggressive and moderate drivers were more likely to exhibit aggressive behavior in HV-AV interaction than in HV-HV interaction, and aggressive drivers had more anxious feelings when interacting with AVs compared to HVs. Driving simulator studies [13, 25, 40, 51, 59] and field experiments [31, 41] were conducted to characterize the behavioral adaptation of human drivers when interacting with AVs. These studies showed that human drivers performed a higher speed and acceleration [31], shorter lane changing duration [25, 40], smaller time headways [13, 40, 41, 51], higher time-to-collision [31], and higher gap acceptance [59] when interacting with AVs compared to HVs.

The HV-AV interaction was explored in various traffic scenarios, such as merging, lane changing, and car-following scenarios. Some studies constructed the one-on-one interaction scenarios between HV and AV [30, 31, 41, 59], while others focused on the interaction between HVs and AV platoons [13, 25, 40, 51]. For example, Rad et al. [40] constructed three different traffic scenarios (base: only HVs; mixed: platoons of 2–3 AVs driving on any lane and mixed with HVs; dedicated lane: platoons of 2–3 AVs driving only on a dedicated lane) in a fixed driving simulator. Their results indicated that in a dedicated lane scenario, drivers in HVs maintained shorter distances behind other cars when following them and were willing to take smaller gaps when changing lanes, as opposed to in mixed and base scenarios.

Almost all the studies above are based on the assumption that AVs have defensive programming and are designed to be law-abiding. Perceiving AVs as being defensive, safe, and compliant with traffic laws may encourage people's intention to take advantage of AVs on the road. Autonomous driving companies have reported that individuals, including pedestrians and human drivers, displayed aggressive behavior towards AVs while they were being tested on public roads [14, 43]. This could result in potential interaction conflicts. AVs have to "learn to be aggressive in the right amount according to culture" [46]. Appropriate aggressiveness has been proven to be desirable to enhance traffic efficiency [53]. Several studies have investigated the potential benefits of human-like driving styles in automated vehicles, aiming to strike a balance between safety and efficiency [2, 15, 49, 63]. Although studies have shown that AVs' driving styles affected human trust and acceptance when driving or riding in AVs [9, 29], little has been done to investigate how AVs' driving styles influence human drivers' decision-making in HVs when they interact with AVs on the road.

2.2 Game Theory in Human-robot Interaction and Traffic

Game theory has revealed numerous aspects of human cooperative behavior and can be used as a framework to study mutual cooperation [3, 5, 11, 52]. Many studies investigated human behavior in one-on-one human-robot interaction [18, 23, 37, 58, 61], particularly regarding how humans interact with robots in comparison to their interactions with other humans. For example, Paeng et al. [37] and Wu et al. [61] investigated whether the individual's decisions were influenced by the agent type they interacted with in a prisoner's dilemma. Their results revealed that humans had a greater degree of trust in robots than other humans. In the prisoner's dilemma, the Nash equilibrium occurs when both players choose to defect, as it is each player's best response regardless of the other's action, leading to a collectively suboptimal outcome.

Interacting with automated vehicles in mixed traffic requires a balance between assertiveness and caution to ensure traffic efficiency and avoid collisions. The chicken game underscores the importance of cooperation and reciprocity by representing conflict situations in which two players can cooperate or defect. In this game, the player who opts for cooperation is labeled as the "chicken," while the other, who chooses not to cooperate, emerges as the winner [54]. A player gets the most benefits if s/he chooses to defect and the opponent chooses to cooperate. The chicken game features multiple Nash equilibria characterized by asymmetric strategies: one player cooperates while the other defects, and vice versa. This strategic structure makes the chicken game a suitable model for understanding and predicting human behavior when interacting with automated vehicles. Although not within the transportation context, researchers have explored human-human/computer/robot interaction using chicken game [23, 58]. For example, Kim et al. [23] utilized iterative chicken games to study players' behavioral patterns in competition with a human or a computer and found that human players altered their behaviors in response to the agent's behavioral pattern and were more sensitive to fairness when they were told to play with a human. Torre et al. [58] revealed that when interacting with robots in the chicken game, human behaviour changes based on robot anthropomorphic level and human perceived autonomy.

Some studies explored human-robot interaction when teaming up with multiple robots [8] or competing against robot groups [12]. Public goods game is a multiplayer experiment used to study the behavior of individuals in a group setting: those who cooperate contribute to the public good, while those who defect do not make any contribution. The total contribution is multiplied by an enhancement factor less than the number of members, and the result is distributed evenly among all members of the group. Hence, defectors get the same benefit as cooperators at no cost [47]. Correia et al. [8] demonstrated the importance of group-oriented decision-making by revealing the positive perceptions of prosocial behavior in human-robot interaction. Additionally, Fraune et al. [12] found that in human-robot interaction, individual-to-individual interaction is more negative and competitive than individual-to-group interaction. They posited that this may not simply be attributed to the traditional motivation of greed and fear. They speculated that the equivalence in size between the robot group and the human group played a significant role in competition behaviors. A series of studies by Tanimoto et al. [35, 56, 57] suggested that social dilemmas may underlie a traffic flow phenomenon. They found that the structures of some traffic cases, including 2 into 1 lane junction (bottleneck), lane changes, and route selection, corresponded to the chicken game and public goods games in game theory.

While behavioral game theory shows great potential to study human-robot interaction, little research has employed game theory to theoretically categorize driving scenarios and investigate their effects on drivers' behaviors and decision-making in mixed-traffic environments.

3 METHOD

We developed an online survey to explore how interaction types, scenario types, vehicle driving styles, time constraints, and driver driving styles impacted driver decisions in mixed-traffic environments. This research complied with the American Psychological Association Code of Ethics and was approved by the institutional review board at the University of Pittsburgh.

3.1 Experimental design

Independent variables. We constructed a study with a $3 \times 2 \times 2 \times 2 \times 2$ mixed factorial design. The between-subjects variables were the driver driving style (aggressive vs. moderate vs. conservative), vehicle driving styles (aggressive vs. conservative), and interaction types (HV-HV vs. HV-AV). Aggressive driving style [62] is associated with faster speed, acceleration, and larger steering wheel rotation angle and angular velocity. Conservative driving style [62] is associated with longer space headway, larger angle of the brake pedal, and longer deceleration. Moderate driving style [62] is associated with relative steady motions that are neither too conservative nor too aggressive. In our experiment, the automation level of AVs is SAE Level 5 (defined by The Society of Automotive Engineers), which means that the automated driving system can drive the vehicle under all conditions, and humans are not required to perform any driving tasks [17]. Drivers' driving style groups were further explained in Section 3.3.

The within-subjects variables were time constraints (high vs. low), and scenario types (chicken game vs. public goods game). Under high time constraints, drivers were requested to reach a destination with utmost haste, whereas they drove without time pressure under low time constraints. We set up four specific high-time-constraint situations to trigger high time pressure among participants: rushing to an important meeting, rushing to an upcoming important interview, catching a flight with limited time, and catching a train with limited time. We conducted a manipulation check on the time constraints by asking participants to evaluate their perception of time pressure (1: not at all; 5: extremely) under each condition. The one-way repeated measures ANOVA analysis showed that the difference in perception of time constraints was significant ($F(1, 673) = 2443.334; Mean_{\text{high}} = 3.605; Mean_{\text{low}} = 1.428; p < .001$).The payoff matrices of the chicken game (Table 3) and the public goods game (Table 4) were presented in Appendix A.1. We did not claim the scenario types or provide the payoff matrices with specific values to participants because individual participants may have varying pay-off values influenced by factors such as their interpretation of scenarios, perceived time pressure, and perceived risk. Each condition was designed using a text description and an animated scenario (see Fig. 1) to help participants understand the context. The order of each condition was random across participants.

Dependent variable. The dependent variable was the participants' decisions. A binary category variable was used to represent the driver's tendency to cooperate or defect. After participants watched each scenario animation, they were given two options (see Table 1 and Figure 1), displaying in a random order. Selecting the option (1) (see Table 1: Possible decisions) indicated cooperation, and selecting the option (2) indicated defection. In addition, in order

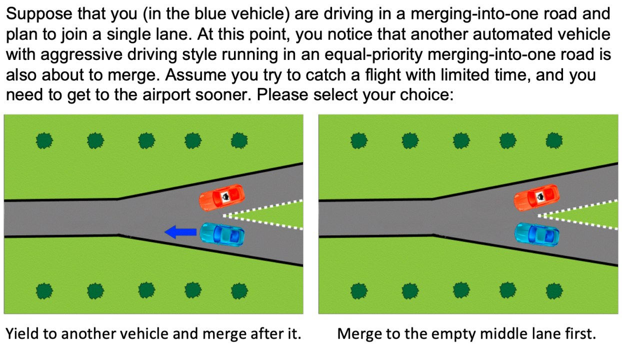


Figure 1: An example of survey questions

to explore drivers' decision-making strategies and related factors, we further set up an open-ended question to ask the reasons for selecting/not selecting the option.

Scenarios. We constructed eight game-theoretical driving scenarios (see Table 1) to test driver decisions in mixed-traffic environments. We created scenarios from a top-down viewpoint to enhance the understanding of the overall traffic situations. In the chicken game scenarios, the subject car (the car participants were driving) and another car competed for the right of way. In the public goods game scenarios, the subject car in the traffic could overtake other vehicles by changing lanes to achieve free riding. In both types of game theoretical scenarios, players had the option to either cooperate or defect to meet their needs.

3.2 Procedure

The consent, instructions, driving scenarios, and questionnaires were integrated into Qualtrics, and the study was launched on the CloudResearch platform [1]. First, participants who met the criteria were randomly assigned to four groups (human-driven vehicles with aggressive driving style, human-driven vehicles with conservative driving style, automated vehicles with aggressive driving style or automated vehicles with conservative driving style). Then they were guided to read the instructions and take the training session. In the instructions, participants were introduced to the definitions of the vehicle driving style and vehicle type associated with their respective groups. In the training session, participants were required to read the introduction of scenarios and answer the attention check questions carefully. If they failed the attention check, the survey would end automatically.

After the training session, participants were asked to imagine themselves as the driver of the HV and make decisions when interacting with either human-driven vehicles or automated vehicles in four conditions (2 types of time constraints × 2 scenario types). For each condition, they were asked to read a text description and watch an animated traffic scenario, and then indicate their preferred decision from two choices. Each participant encountered 2 chicken game scenarios and 2 public goods scenarios (1 under high time constraints and 1 under low time constraints in each scenario type). These scenarios were created by random sampling without replacement from 4 chicken game scenarios and 4 public goods game scenarios. After making the decision, participants were asked to assess the anticipated time pressure in the given scenario and answer the open-ended question. In the end, participants reported their demographic information, the propensity to trust automated vehicles [32] and answered the violation subscale of Driving Behavior Questionnaire (DBQ) [44].

3.3 Participants

A total of 686 people were recruited from the CloudResearch platform and based on the United States Census template. We obtained informed consent from each participant. We screened them for various inclusion criteria including 18 years or older, driver's license status, and non-colorblind. We deleted the data of participants who timed out (we set the completion time as 80 minutes), submitted in less than 5 minutes using the incorrect link, or failed the attention check. At last, 674 qualified people (336 females, 338 males) participated in the study. Participants were paid \$3 for their participation in the 20-minute online survey study. The participants' ages ranged from 18 to 80 with an average age of 45.88 years (SD=15.5 years). Propensity to trust automated vehicle scale included 6 items rated on five-point rating scales (1: strongly disagree; 5: strongly agree). A higher score indicates a greater propensity to trust automated vehicles. Participants' average trust propensity was 2.69 (SD=1.13).

We characterized drivers' driving styles into three categories [21, 28, 62] based on the scores in the adapted violation subscale of DBQ. All the 12 items were rated on six-point rating scales (1: never; 6: nearly all the time). Existing studies [16, 64] indicated drivers with high DBQ violation scores showed more aggressive objective driving behavior. We divided our participants into three groups based on the 33rd percentile and the 66th percentile [22, 38, 55]: aggressive (223 participants; score>23: $\mu = 30.55, \sigma = 7.08$), moderate (191 participants; 19<=score<=23: $\mu = 20.94, \sigma = 1.43$), and conservative (260 participants; score<=18: $\mu = 15.51, \sigma = 2.04$) drivers. There were 170 participants assigned to interact with HVs with conservative driving styles, 170 participants with HVs with aggressive driving styles, 170 participants with AVs with conservative driving styles, and 164 participants with AVs with aggressive driving styles.

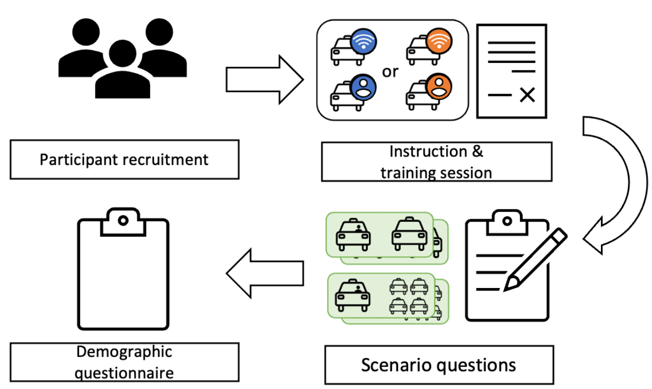
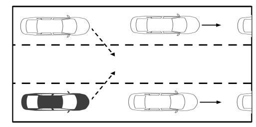
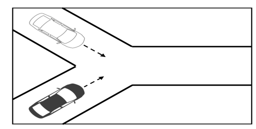
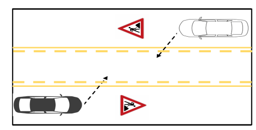
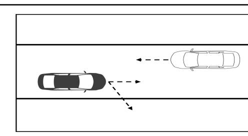
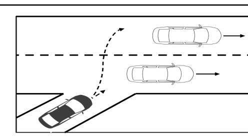
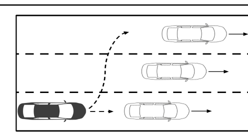
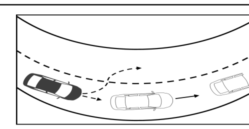
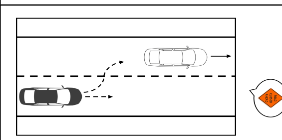


Figure 2: A diagram of the experiment procedure.

[1]The Qualitrics online survey platform is at https://www.qualtrics.com and the CloudResearch participant recruitment platform is at https://www.cloudresearch.com/

Table 1: An overview of our eight game theoretic driving scenarios. Chicken game and public goods game each have four scenarios. S1-S4 belong to the chicken game, S5-S8 belong to the public goods game. For each scenario, we provide a description, two possible decisions (option (1) represents defection, option (2) represents cooperation), and a diagram. In each diagram, the black vehicle represents the ego vehicle.

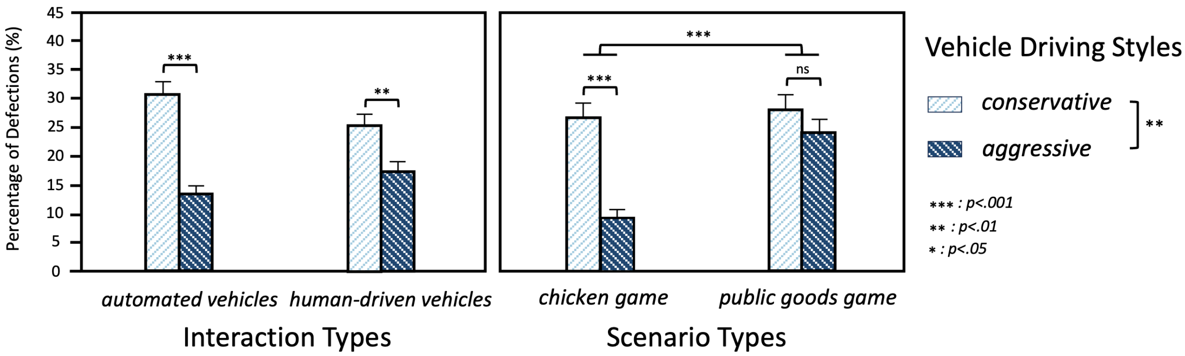
Abstract game	Scenario description	Possible decision	Diagram
Chicken game	S1. Two vehicles in the most-right and most-left lanes of a three-lane road, are slowed down by the traffic ahead, and plan to switch to the empty middle lane.	(1) switch to the empty middle lane first, or (2) yield to another vehicle and switch after it.	
	S2. Two vehicles on two equal-priority merging-into-one roads trying to join the single road (like an inverted fork).	(1) merge into one road first, or (2) yield to another vehicle and then merge.	
	S3. On a three-lane, two-way road, two vehicles are running in the most-right and most-left lanes in the opposite directions. They both need to encroach on the same middle lane to pass an obstruction.	(1) try to change to the middle lane first, or (2) wait until the other vehicle passes	
	S4. Two vehicles are heading towards each other on a narrow two-way traffic road	(1) continue forward assuming the opposing vehicle will yield, or (2) yield to the opposing vehicle by reversing or swerving onto the sidewalk	
Public Goods Game	S5. A vehicle is joining a two-lane road with the aim of turning right at the next exit. The right-line is a right-turn-only lane and is the slower lane of the two.	(1) join the (slower) right lane first, or (2) continue ahead on the (faster) left lane and make its way in front of other vehicles on the right-hand lane.	
	S6. Driving in traffic congestion.	(1) adhere to speed limits and remain in your lane, or (2) swerve between lanes when gaps between vehicles emerge.	
	S7. In a two-lane roundabout, a vehicle is running in the right lane with heavy traffic and aims to exit at the third exit. The left lane has lower to empty traffic.	(1) change to the left lane first and merge into the right lane before exit, or (2) remain in the right lane.	
	S8. A vehicle is running in the empty right lane but the right lane is closed ahead. The left lane has heavy traffic and is the slower lane.	(1) change to the left lane once knowing the right lane is closed, or (2) remain in the right lane and merge to the left lane when close to the closure.	

4 RESULTS

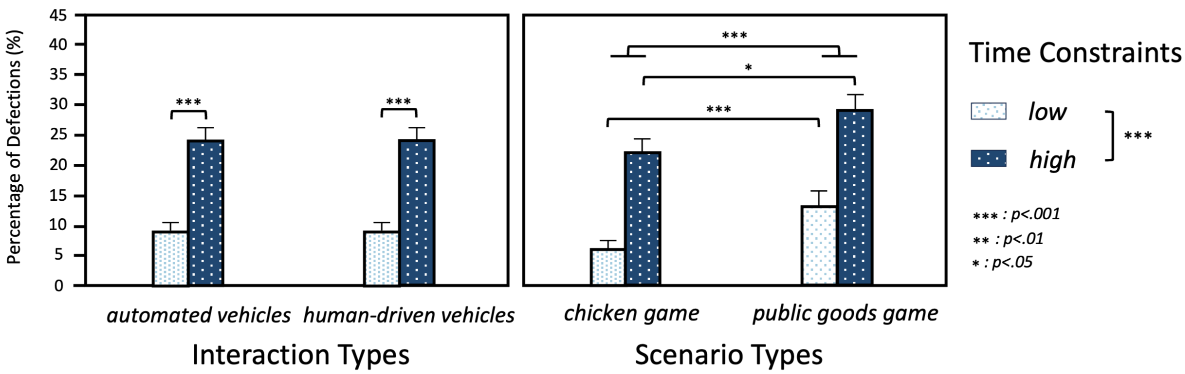
4.1 Effects on Decisions

Statistical analysis was performed using IBM SPSS Statistics Version 28.0. Due to the repeated measurements and the binary responses, Generalized Estimating Equations (GEE) were constructed to analyze the effects of independent variables (vehicle driving styles, interaction types, time constraints, scenario types, and driver driving styles) on the dependent variable (driver decisions). We included the independent variables and their two-way interactions as factors in the GEE model. We specified Binomial as distribution, Logit as the link function, and Bonferroni for multiple comparisons adjustment.

4.1.1 Main Effects. The test of model effects showed that there were significant main effects of vehicle driving styles ($\chi^2(1)$ =



(a) The main effect of vehicle driving styles was significant ($p < .01$). (Left) Vehicle Driving Styles and Interaction Types. In the HV-AV interaction, the difference in the percentage of defections between vehicle driving styles was greater than in the HV-HV interaction ($p < .001, p < .01$). The percentages of defections were higher when interacting with vehicles with conservative driving styles in both interaction types. (Right) Vehicle Driving Styles and Scenario Types. The main effect of scenario types was significant ($p < .001$). We only observed significant difference in the percentage of defections between vehicle driving styles in the chicken game ($p < .001$).



(b) The main effect of time constraints was significant ($p < .001$). (Left) Time Constraints and Interaction Types. There was no interaction effects between interaction types and time constraints. (Right) Time Constraints and Scenario Types. The main effect of scenario types was significant ($p < .001$). The percentages of defections were higher in public goods game than in chicken game under both time constraints. Under low time constraints, the difference in percentage of defections between scenario types was greater than under high time constraints ($p < .001, p < .05$).

Figure 3: The interaction effect results (Error bars indicate 1 standard error [SE])

27.32; $p < .001$), time constraints ($\chi^2(1) = 123.357; p < .001$), scenario types ($\chi^2(1) = 27.797; p < .001$), and driver driving styles ($\chi^2(2) = 52.013; p < .001$) on driver decisions. The main effect of interaction types was not significant ($\chi^2(1) = 2.748; p = .097$).

The main effects indicated that drivers defected more when interacting with vehicles that have a conservative driving style. Additionally, drivers were more inclined to defect when under high time constraints. In the public goods scenarios, their decisions leaned more towards defection. We also examined the effect of the individual scenario. Drivers exhibited more defections ($p < .001$) in Scenario 6 (S6 in Table 1) and Scenario 8 (S8 in Table 1) in public goods game. Regarding driver driving styles, the propensity for defection increased from conservative to moderate and was highest among aggressive drivers.

4.1.2 Interaction Effects. There were significant interaction effects between vehicle driving styles and interaction types ($\chi^2(1) = 5.703; p = .017$), between vehicle driving styles and scenario types ($\chi^2(1) = 25.165; p < .001$), between time constraints and scenario types ($\chi^2(1) = 6.254; p = .012$), and between interaction types and driver driving styles ($\chi^2(2) = 6.812; p = .033$). All the other effects were not significant. Below we further explain the interaction effects in detail.

Vehicle Driving Styles × Interaction Types. The significant interaction effect between vehicle driving styles and interaction types on driver decisions (see Fig. 3a) suggested that both in HV-AV interaction and HV-HV interaction, drivers had a higher chance of defections interacting with vehicles with conservative driving styles than aggressive driving styles ($p < .001$, $p = .005$). Yet, in the HV-AV interaction, the impact of vehicle driving styles was greater than in the HV-HV interaction.

Vehicle Driving Styles × Scenario Types. The significant interaction effect between vehicle driving styles and scenario types on driver decisions (see Fig. 3a) indicated that drivers were more likely to defect when interacting with a conservative vehicle driving style versus an aggressive driving style in the chicken game scenarios ($p < .001$). Yet, in the public goods game, the effect of vehicle driving styles on driver decision-making was not significant ($p = .634$).

Time Constraints × Scenario Types. The significant interaction effect between time constraints and scenario types (see Fig. 3b) showed that in public goods games, the percentage of defection was higher than in chicken games under both low and high time constraints ($p < .001$, $p = .027$). While under low time constraints, the impact of scenario types was greater than under high time constraints.

Interaction Types × Driver Driving Styles. The significant interaction effect between interaction types and driver driving styles (see Fig. 4) showed that the significantly more defections in HV-AV interaction only existed in drivers with moderate driving styles ($p = .036$).

4.2 Qualitative Results

To better understand how drivers make decisions in mixed traffic, we collected their responses to an open-ended question: "Please describe your reasons for selecting *option A* (the text of their selected option) and reasons for not selecting *option B* (the text of their non-selected option)." Each participant provided a total of four responses, answering this question once after each scenario. We removed 16 responses from 4 participants due to the poor quality including incomplete sentences, providing the same answer for different scenarios, and meaningless answers made to meet the word limit. Our final analysis used 2680 responses from 670 participants. To construct participants' decision-making rationale, we employed an inductive approach to conduct thematic analysis [4]. Two annotators independently read the responses and conducted open coding to identify the categories. The annotators and authors then discussed the existing disputes and overlaps, ultimately refining and finalizing the main themes and sub-themes.

We identified two main themes to define the decision-making process reflected in participants' responses: perception factor and strategy. Table 2 showed the framework and Table 5 in Appendix A.2 served as the codebook that further described each strategy and their examples. Under the perception factor, we examined what kind of conditions and scenarios influenced drivers' decisions. We found that "reaching the destination within a time limit" was not perceived as a benefit. Instead, participants viewed failing to reach the destination on time as a loss. For example, P431 mentioned that *"It sounds as though this job interview is important and I cannot afford to be late."* This aligns with the prospect theory of Kahneman and Tversky (1979), which indicates that loss aversion causes individuals to weigh losses more heavily than gains relative to the reference point [20, 50]. This structured the game-theoretic loss framework of our design. Under the strategy, we identified four criteria that participants depended on when making decisions. Considering the outcomes of cooperation and defection, 64% responses adopted risk aversion (41%) and loss aversion (23%) given the trade-off. 9% responses showed that the decisions stemmed from drivers' attitudes towards other vehicles. 27% decisions were made based on participants' driving styles and habits. Below we discussed each strategy in detail.

4.2.1 *Trade-off in loss-frame game theory.*

In general, we assumed that defection reduced time losses, and cooperation carried no safety risks. However, participants held varied views of loss and risk through cooperation or defection, which was determined by their perceptions of the mixed traffic. Regarding the perception of loss, some drivers believed that defection did not lead to time losses. Some drivers argued that defecting did not necessarily mitigate time losses in the chicken game, like what P313 said, *"There would be no advantage gained by getting in the left lane, since I'd just have to get back into the right lane anyway"*. This occurred more frequently in scenarios S5 and S7 (two-lane exit). A subset of drivers were of the opinion that under low time constraints, cooperation would not lead to time loss. Concerning the perception of risk, some other drivers thought that defection came with risks and would cause an accident, like what P433 said, *"There's a chance of getting in an accident if you try and force the lane change."* However, some drivers felt that cooperation was less safe than defection in some scenarios such as S6 and S8. In S8, P223 said, *"I'd rather stay in the right lane than get in with the aggressive drivers."* This explained the variance we observed between public goods game scenarios. In summary, based on participants' diverse perceptions, we found that defection can either reduce time losses or have no influence on time, can be associated with safety risks, yet can also be safe in the public goods game scenarios. Cooperation can either increase time losses or have no impact on time, can be safe, but can also entail risks in public goods game scenarios. These differences were driven by participants' varying interpretation of scenarios, perceived time pressure, and perceived risk. Individuals constructed their own payoff values based on these factors, which led them to behave as rational economic men when making the decisions. Therefore, varying payoff structure ultimately achieved two results, cooperate and defect, through four trade-off categories: safety risks, time losses, no influences on time, and time losses and safety risks (see Table 2, Fig. 5).

After discerning the losses and risks, drivers subsequently employed two strategies based on the perceptions: risk aversion and loss aversion. If they perceived cooperation as leading to time losses (19%), they leaned towards defection (see Fig. 5). If they felt that defection would not substantially reduce time losses (12%), they tended to cooperate. When faced with a situation where cooperation or defection could potentially introduce safety risks (16%), drivers generally prefer cooperation. Moreover, when cooperative behavior resulted in time losses but defection carried safety risks (13%), drivers weighed the losses and risks. When drivers prioritize time and the negative consequences of time losses, they may be willing to take on risks (2%). For example, P383 said, *"Because I am in a hurry ... I am aware that the other driver is driving with an aggressive driving style. I would try to out maneuver the other driver ... ."* On the other hand, to ensure safety or prevent the potential exacerbation of losses due to accidents, drivers opted for risk aversion, as mentioned by P509, *"If I get into the left lane and the exit is coming up soon, I may have trouble merging back into the right lane ... resulting in me missing my exit and being even later."*

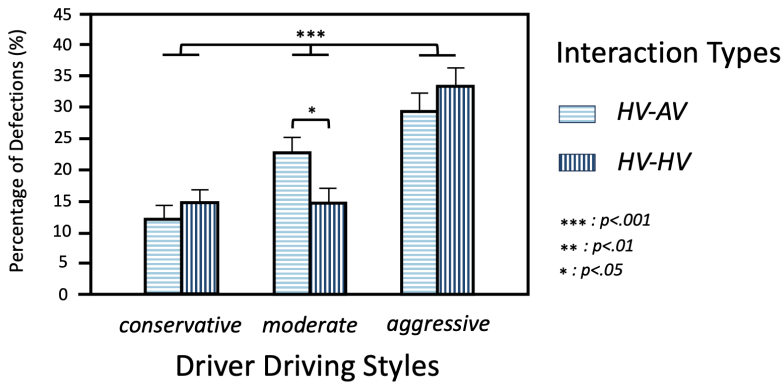


Figure 4: The interaction effect between interaction types and driver driving styles.

Table 2: An overview of identified themes, sub-themes, and their descriptions and dimensions with the number of responses for the open-ended question.

Theme	Sub-theme	Description & Dimension	#Response
Perception Factor (overlapping)	A. Conditions	Independent variables mentioned by participants influence decision-making (e.g., aggressive, conservative, in a hurry, not in a hurry, AVs)	2385 (89%)
	B. Scenarios	Scenarios mentioned by participants influence decision-making (e.g., two-lane exit, one-on-one interaction, heavy traffic, empty lane)	2037 (76%)
Strategy	A. Risk aversion	Prioritize risk avoidance given: a) Safety risks; b) Time losses and safety risks; c) No influences on time	1099 (41%)
	B. Loss aversion	Minimize time losses given: a) Time losses; b) Time losses and safety risks	616 (23%)
	C. Attitudes towards others	Make decisions based on drivers' attitudes towards other vehicles: a) Positive; b) Negative	241 (9%)
	D. Own driving styles and habits	Make decisions based on driver's driving styles and habits: a) Style and preference; b) Experience and habit; c) Manner and rule adherence	724 (27%)

4.2.2 *Varied attitudes towards other vehicles.* In 9% of the responses, participants' decisions were directly related to their attitudes towards other vehicles (AVs or all others). Some participants maintained a consistent attitude toward other vehicles, unaffected by the conditions, such as *"I don't trust the other drivers"* (e.g., P96, P148). Others expressed their opinions based on their perceived information from mixed traffic. Classifying attitudes from positive and negative perspectives, 2% responses indicated a positive stance, with participants placing trust in other vehicles and feeling confident that they would cooperate. These participants consistently chose to defect. In contrast, some other drivers held negative attitudes (7%), expressing distrust and skepticism. They chose to take control of their own destiny, such as assuming others would not yield and thus yield themselves.

Specifically, participants had varied attitudes and expectations regarding AVs, which led to their distinct decisions. Drivers who distrusted AVs (4%) far outnumbered those who trusted them (0.7%), because many people found the behavior of AVs to be unpredictable. Some even thought AVs were harmful, as P31 said, *"I will yield to the automated vehicle because its driving is dangerous..."* An aggressive driving style of AVs only heightened such sentiments, like what P533 stated, *"I don't trust that an automated car (especially driving aggressively) could possibly yield as effectively as a human would."* Individuals classified themselves and AVs into various social categories, leading to bias and prejudice. Drivers viewed AVs as "machines" that should yield to human drivers on the road and bullied AVs. For example, P519 said, *"May as well abuse their programming and get ahead. Machines can wait."* Notably, there was an urgent need for human drivers to have effective communications with AVs, as emphasized by P201 and P556, *"I have no way to hand signal to the automated vehicle, because there is no driver."*

4.2.3 *Make decisions based on drivers' driving styles and habits.* 27% decisions were made based on drivers' driving styles and habits. We coded them into three categories: style and preference, experience and habit, and manner and adherence. In 13% responses, participants maintained their driving style regardless of the conditions. A subset of drivers expressed their preference for a more leisurely driving style, seeking relaxation and simplicity. They enjoyed "listening to audio books while driving" and leaned towards "simpler and easier" maneuvers. 9% responses anchored their decisions to past experiences and ingrained habits. 5% advocated for politeness and prioritized strict adherence to established road rules.

4.2.4 *Why do drivers defect?*

Figure 5 showed the mapping from dimensions to strategies and then to decision outcomes. The story told us that while drivers considered various factors and employed distinct strategies during decision-making, the majority still gravitated towards cooperation. The main reason for cooperation is to avoid safety risks, followed by one's driving styles and habits, as well as attitudes toward other vehicles. The primary motivations for defecting were: minimizing the time losses, avoiding risks, and positive attitudes towards other vehicles. Although drivers made different decisions when weighing losses and risks (see Figure 5, Dimension, Time Losses with Safety Risks), a mere 2% chose to embrace the risk in order to reduce the loss. It is crucial to understand and predict the behavior of this small fraction.

5 DISCUSSION

Our research revealed the significance of the vehicle driving styles for human drivers' decisions when they interacted with AVs and HVs (RQ1). Varying types of game-theoretic driving scenarios interacted with time constraints and vehicle driving styles to influence drivers' decisions (RQ2). Moreover, we gained insight into how drivers extract information from those scenarios and formulate strategies for decision-making (RQ3). Below we discuss the results, the design implications, and the limitations and future work.

5.1 Driver decisions when interacting with AVs vs. HVs

Our findings highlight that the driving style of the interacting vehicle holds a more substantial influence than whether the interacting vehicle is human-driven or automated. Our results indicated that a vehicle's driving style significantly impacted the driver's decision-making, with drivers performing more defective behaviors when interacting with vehicles with conservative driving styles. Additionally, drivers exhibited varying behaviors when interacting with AVs with different driving styles, a distinction less pronounced with HVs. One possible explanation is that AVs may accentuate disparities between vehicle driving styles. Compared with the HVs of the same driving style, drivers might exploit AVs of conservative driving styles more, anticipating their likelihood to yield, and exercise more caution when interacting with aggressive AVs due to their unpredictability. Our results were consistent with GATEway project 2017 [24]. This study indicated that driving decisions were predominantly influenced by factors like gap size and safety evaluations, which were reflected in driving style, rather than the presence of AVs or HVs. Similarly, our qualitative results indicated that first, in mixed traffic, the interaction type took a lower priority in human drivers' information processing, with drivers prioritizing traffic conditions and personal needs. Additionally, human drivers had varying views and expectations regarding AVs. The underlying reason might be the agency and subjectivity of AV has not been acknowledged. The mental model developed by Liu [26] considered human and machine drivers as heterogeneous and incompatible. Even though we emphasized AVs in traffic were fully autonomous at SAE Level 5, human drivers held reservations about AVs' level of intelligence.

We found that the effects of time constraints were similar in HV-AV interaction and HV-HV interaction. However, Trende et al. [59] discovered that under high time pressure, people may take more advantage of AVs than HVs. One possible explanation for this discrepancy could be that their participants were informed that AVs drove more cautiously than HVs but our study posited that besides the driving modes, both AVs and HVs had the potential to exhibit aggressive or conservative driving styles. Additionally, our work considered more situations and our results were more generalizable. For example, our participants were exposed to a variety of scenarios, while their participants only experienced a specific right and left turn at an intersection scenario. Also, our participants were from different age and occupation groups but their participants were relatively young with an academic background.

Furthermore, drivers' decisions often align with their intrinsic driving styles. Our statistical results revealed the distinct patterns among three categories of drivers: conservative, moderate, and aggressive. Aggressive drivers tended to defect more than relatively conservative drivers. Specifically, in HV-AV interaction, both moderate and aggressive drivers exhibited defection; in HV-HV interaction, both conservative and aggressive were more cooperative. It appeared that conservative drivers and aggressive drivers did not change their behaviors while moderate drivers might adjust their behaviors based on the type of vehicle they are interacting with. It indicated that drivers with extreme driving styles consistently adhered to their driving styles, regardless of external factors. We did not find a significant difference in decisions towards AVs and HVs among aggressive drivers or among conservative drivers, which seemed different from Ma and Zhang [30]. Their results suggested that aggressive drivers were more likely to take advantage of interacting vehicles in HV-AV interaction than in HV-HV interaction. One big difference between these two studies is that the driving styles of AVs could be either aggressive or conservative in our study but were coded to drive cautiously in their study.

5.2 Driver decisions in varying game-theoretical driving scenarios

To expand the existing studies, we employed the chicken game and public goods game in game theory to develop two types of driving scenarios. Our results suggested that drivers were more likely to cooperate in chicken game scenarios compared to public goods game scenarios. This is consistent with traditional game theory, which posits that two-person games like the chicken game encourage more cooperation, and are inherently different from games involving three or more players [34].

However, this differs from the phenomenon mentioned in a human-robot interaction study [12], which constructed a one-on-one chicken game and a one-on-group chicken game to examine how the number of robots affects human behavioral competition in dilemma tasks. Their results showed that the number of robots had no effect on the competitive behavior of humans. However, our research showed behavioral variances between the chicken game scenarios and the public goods game scenarios. This discrepancy might stem from the fact that in mixed traffic, the human driver's perception of the scenarios does not solely depend on the number of interacting vehicles, but on the complexity and payoff structure changes caused by the number of interacting vehicles. Also, it is worth noting that driving is fundamentally rooted in safety, and the game-theoretical results from human-robot interaction may not be

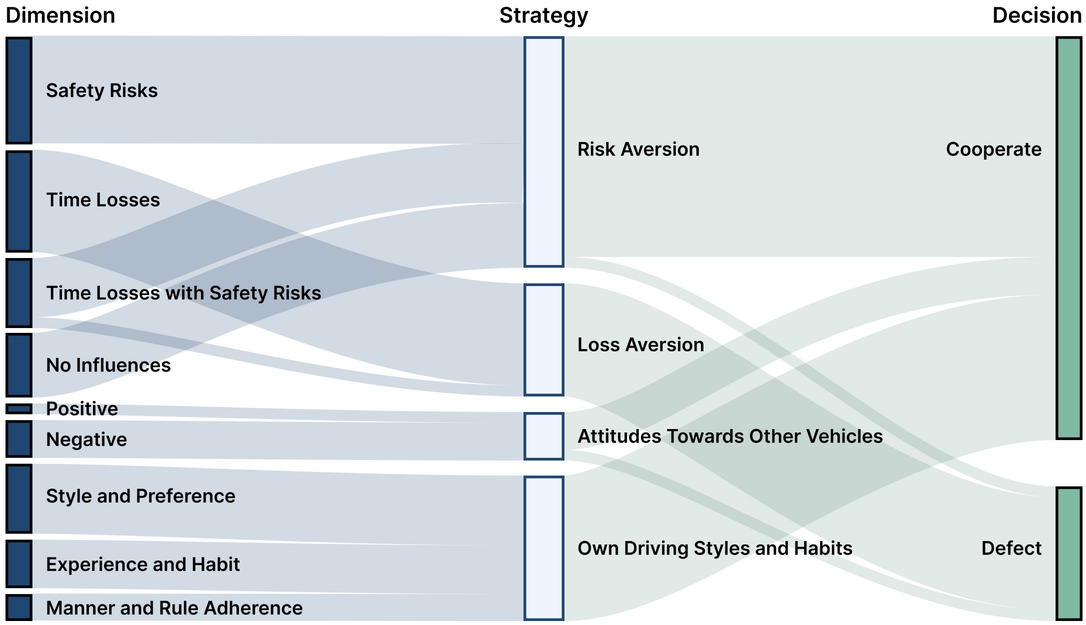


Figure 5: Why do drivers defect? A mapping that reflects the dynamic relationship from dimensions to strategies to decisions when drivers make decisions.

directly applied to interactions between human drivers and AVs in a mixed-traffic environment. Our findings confirmed this. From the qualitative results, one possible reason for differences between the two types of games could be that in our scenario design, chicken game scenarios posed greater risks than public goods scenarios due to the immediate danger of head-on collisions. Drivers in the chicken game scenarios exhibited higher levels of risk aversion. In the chicken game scenarios, drivers showed more willingness to cooperate when confronted with vehicles of aggressive driving styles compared to vehicles of conservative driving styles. This trend was not observed in the public goods scenarios. Participants notably exhibited more cooperation only when encountering vehicles with aggressive driving styles in chicken game scenarios. The aggressive driving style heightened the risk of chicken game scenarios and further intensified drivers' risk aversion in decision-making.

Under high time constraints, drivers exhibited a higher tendency to defect. This indicated that when losses occurred, drivers chose to prioritize minimizing these losses. Meanwhile, under high time constraints, we found that drivers were more likely to defect in both scenario types compared to low time constraints, whereas the gap between different scenario types was narrow compared to low time constraint conditions. A possible explanation for these results is that drivers amplified the negative outcomes of time losses under high time constraints. Therefore, even if defection carried significant risks, drivers were more inclined to take those risks to mitigate time losses. In essence, under high time constraints, loss aversion outweighed risk aversion, potentially reducing the variances introduced by the different scenarios.

5.3 Implications for AV and System Design

This study highlights the need to understand the direct and indirect influence of AV programming (and their driving styles) on the overall driving behavior of humans on the road. AV programming should strike a balance, avoiding being excessively conservative while also not being easily bullied by other vehicles. Recognizing the diverse perceptions and expectations people have regarding vehicle types and driving styles, it is important for manufacturers and regulators to either standardize certain behaviors or clearly define AV's driving styles. AV design should prioritize dynamic adaptability to human drivers' driving styles and be equipped with mechanisms for recognizing and responding to human drivers appropriately. While spotlighting the potential of integrating driving styles into AV design, it also highlights the ethical responsibilities that accompany such technological advancements. We are committed to a careful exploration of these issues in our ongoing and future work.

Our findings have significant implications for the development of driver behavior prediction systems, which could predict driver behaviors and decision-making when interacting with AVs in novel situations. This indicates that various aspects of human drivers, including their personal needs, risk perceptions, attitudes, expectations towards other vehicles, and their own driving styles, could serve as key predictive factors. Additionally, this study emphasizes the importance of developing innovative communication methods between HVs and AVs. For example, designing human-machine interfaces to communicate AV intentions and offer driving strategy suggestions to drivers could be beneficial. Lastly, future traffic regulations and public policies should delve deeper into defining the rights and responsibilities of AVs in mixed traffic environments.

6 LIMITATIONS & FUTURE WORK

There are some limitations in our work. First, our sample was geographically limited to the United States, which may not represent the perceptions and behaviors of other populations in distinct regions. To gain a more comprehensive understanding, cross-country research would be necessary in the future. The use of different countries will help establish the external validity of the findings across a wide-set of countries. Second, our game theoretical scenarios and settings were described using text and animations, and participants' decisions were collected from web-based questionnaires. In such settings, we were only able to investigate participants' hypothetical responses. Future research can employ driving simulator studies and on-road testing to immerse participants in interactions with various vehicle types and driving styles, examining their revealed decisions, such as driving strategies and performance in the dynamic environment. Third, future research could develop more scenarios and manipulate more interaction settings (e.g., number of passengers, vehicle automation level, vehicle brand) and driving environments (e.g., geographical locations, weather, and light conditions) to investigate human-machine cooperation in more diverse mixed-traffic environments.

7 CONCLUSION

This study investigated how the driver and vehicle driving styles, interaction types, scenario types, and time constraints influenced human drivers' decision-making in mixed-traffic environments and provided insights into how drivers perceived conditions and formulated strategies for decision-making. First, in the HV-AV interaction, the difference between conservative and aggressive vehicle driving styles was more pronounced than in the HV-HV interaction. Drivers defected more when interacting with vehicles with conservative driving styles. Second, in the chicken game scenarios, drivers cooperate more when encountering vehicles with aggressive driving styles. While such differences did not exist in the public goods game scenarios. Third, drivers tended to defect more in the public goods game scenarios or under high time constraints. Yet, compared to the low time constraints, the difference between scenario types narrowed. We also identified that human drivers adopted four strategies, including risk aversion, loss aversion, attitudes towards others, and own driving styles and habits to make decisions in the mixed traffic. Our findings provide essential insights into AV algorithm design and the implementation of future human-machine systems from human aspects to facilitate human-machine cooperation in mixed-traffic environments.

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A APPENDIX A

Table 3: Payoff matrix of the chicken game, played by pairs. First payoff is for Player i, the second is for Player j. Payoffs are represented as Tie, Win, Lose, Crash, with $Win > Tie > Lose > Crash$.

		Player j	
		Cooperate	*Defect*
Player i	*Cooperate*	Tie, Tie	$Lose, Win$
	Defect	$Win, Lose$	$Crash, Crash$

Table 4: Payoff matrix of the public goods game, played by a group of k players. Payoffs are for Player i. Payoffs are represented as $a_j = r.c.\frac{j+1}{k} - c$ and $b_j = \frac{r.c.j}{k}$, where $j = 0, ..., k-1$ is the players $-i$ who chose cooperation, r is the multiplier (with $1 < r < k$), and c is the cost of cooperation. For simplicity, we choose $c = 1$ and $r = \frac{k+1}{2}$.

		Player −i				
		k-1	k-2	...	1	0
Player i	*Cooperate*	a_{k-1}	a_{k-2}	...	a_1	a_0
	Defect	b_{k-1}	b_{k-2}	...	b_1	b_0

Table 5: Codebook for sub-themes and dimensions

Strategy (Sub-theme)	**Dimension**	**Description & Example**
Risk aversion	Safety risks	Participants prioritized risk avoidance given safety risks. *e.g., "There's a chance of getting in an accident if you try and force the lane change."*
	Time losses and safety risks	Participants prioritized risk avoidance by weighing time losses and safety risks. *e.g., "If I get into the left lane and the exit is coming up soon, I may have trouble merging back into the right lane–or possibly be unable to merge, resulting in me missing my exit and being even later."*
	No influences on time	Participants prioritized risk avoidance due to there was no influences on time. *e.g., "There would be no advantage gained by getting in the left lane, since I'd just have to get back into the right lane anyway."*
Loss aversion	Time losses	Participants minimized time losses. *e.g., "I chose to swerve between lanes ... because I don't want to waste all day arriving at my location."*
	Time losses and safety risks	Participants minimized time losses after weighing time losses and safety risks. *e.g., "Because I am in a hurry ... I am aware that the other driver is driving with an aggressive driving style. I would try to out maneuver the other driver ... by increasing my velocity and in sharply."*
Attitudes towards others	Positive	Participants placed trust in other vehicles and felt confident that they would cooperate. *e.g., "I believe the automated car will yield to me."*
	Negative	Participants expressed distrust and skepticism on other vehicles as assuming others would not yield. *e.g., "I don't trust other vehicles."*
Own driving styles and habits	Styles and preference	Participants maintained their driving style regardless of the conditions or expressed their preference. *e.g., "I was taught how to drive defensively so will always opt to avoid possible accidents."*
	Experience and habit	Participants anchored their decisions to past experiences and ingrained habits. *e.g., "It's always better to do that in a roundabout and I know that from experience."*
	Manner and rule adherence	Participants advocated for driving manner and prioritized strict adherence to established road rules. *e.g., "Turning wide is technically illegal even though many people do it."*