Modelling Implicit and Explicit Communication Between Road Users from a Non-Cooperative Game-Theoretic Perspective: An Exploratory Study

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Abstract: Road user interaction is a fertile avenue for communication between road users, be it implicit communication or explicit signals sent with the intent to convey information. To date, most literature on characterising and modelling communication between road users has focussed on cooperative paradigms and concepts of shared goals enforced globally on communicating agents. In this paper, we argue that non-cooperative game theory can be used to characterise and model effective and mutually beneficial communication between road users. We demonstrate that non-cooperative game theory can produce meaningful improvements in payoffs and interaction safety for both the sender and recipient of communication as an emergent phenomenon.

1 INTRODUCTION

The reciprocal interaction between road users is a fundamental part of the transport experience. The modelling of such interaction is a rapidly growing field. Game-theoretic models are one paradigm in which interaction is studied (Ali et al., 2019; Elvik, 2014; Ji & Levinson, 2020; Kita, 1999), especially from an autonomous vehicle's perspective (Bitar et al., 2022, 2023; Camara et al., 2019). Yet, few such models pay attention to *communication* as a participatory component of road user interaction. In fact, recent work on road user communication as an active component of interaction rejects the game-theoretic approach in part due to its perception as a framework that does not lend itself to communicative behaviour (Siebinga et al., 2023). Instead, the researchers rely on an underlying assumption of the existence of a *shared goal* between interacting players. Yet, non-cooperative game theory has been extensively used to describe and explain emergent cooperative and communicative behaviour in nature, economics, society, and networking (Axelrod & Hamilton, 1981; Fernández Domingos et al., 2017; Orzan et al., 2023; Rubenstein & Kealey, 2010; Stewart & Plotkin, 2013). In this paper, we argue that non-cooperative game theory is a suitable framework for modelling and describing communicative behaviour between road users. We also argue that it can produce beneficial cooperative behaviour as an emergent property which does not require assumptions of common goals or shared values.

We test three hypotheses in this study: 1) vehicles have a selfish incentive to send communication (explicit); 2) vehicles have a selfish incentive to respond to communication (implicit and explicit); and 3) non-cooperative game theory can produce meaningful, cooperative communication as an emergent phenomenon which brings population-wide benefits, quantified by: (a) average population payoff; (b) number of crashes; and (c) number of near misses (defined as interactions with $\min_{x \in T} HW_x \leq 0.5\ s$).

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2 METHOD

2.1 The Interaction Model

We conceptualise interactions as part of a lane-change scenario. The interaction is a two-player, sequential, non-cooperative game in which the Main-lane Vehicle M moves first, followed by a response from the Joining Vehicle J. The game is one of imperfect information (Harsanyi, 1968). We introduce two Bayesian elements and provide a pathway to update beliefs based on communication: $attention$ and $intention$. $Attention$ (values: $attentive/distracted$) relates to whether Vehicle M is aware of and responsive to Vehicle J's movement. $Intention$ (values: $cooperative/punitive$) relates to whether Vehicle M is willing to accept a lane-change if it is not in its favour. Both properties are determined by $Nature$ with a pre-defined probability p for $attentive$ and q for $cooperative$. M has prior knowledge of its own $intention$ and will use this knowledge in its decision-making. It does not have knowledge of its own $attention$, and therefore this attribute does not factor into the decision. If Vehicle M is $distracted$, it has a further chance r to be $fully\ distracted$ and not take any action.

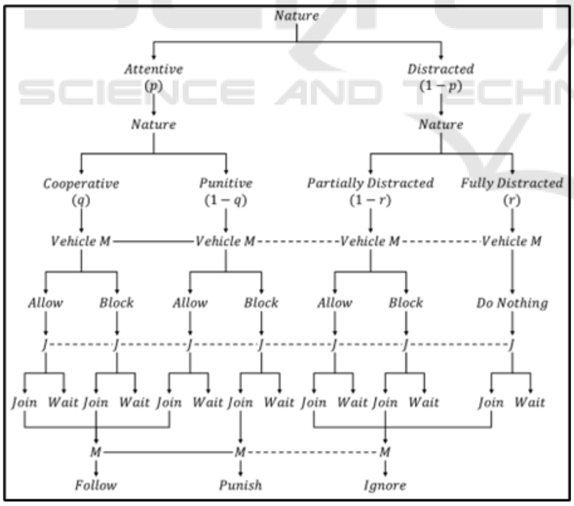

Figure 1: The extensive form sequential game between the Main-lane Vehicle M and the Joining Vehicle J (game tree).

The game continues as shown in Figure 1. A $follow$ action means Vehicle M keeps a suitable time headway. A $punish$ action means M tailgates J to induce a negative utility. An $ignore$ action means M continues moving as if it were in free flow and does not take measures to prevent a collision. The distraction state only lasts a finite amount of time, after which Vehicle M employs the equivalent $attentive$ action (i.e. $follow$ or $punish$).

2.2 The Kinematic Model

Each vehicle possesses a set of attributes and preferences unique to it. We explore the ranges used for these properties in this study in the Experimental Design section. The general movement of the two vehicles is governed by a modified version of the bi-directional General Motors (GM) Car Following Model (Jin et al., 2013), which calculates the acceleration of the following vehicle x at timestep n as follows:

$$a_{x_{n+1}} = \frac{\propto_x \left(v_{x_n}\right)^m}{{\Delta s_n}^l} \Delta v_n \quad (1)$$

where:

$a_{x_{n+1}}$ is the acceleration of the agent vehicle x at the end of the next timestep $n+1$.

v_{x_n} is the velocity of the agent vehicle x at the current timestep n.

Δs_n is the distance difference between the agent vehicle and its car-following target at timestep n.

Δv_n is the velocity difference between the agent vehicle and its car-following target at timestep n.

$\propto_x$ is a sensitivity factor which governs the agent vehicle x's corrective acceleration rate to maintain car-following headway. The higher the sensitivity factor, the more aggressive the correction.

m, l are parametric sensitivity factors which in this study are set to 1.

$a_{x_{n+1}}$ is constrained by the agent vehicle's acceleration preferences and physical limitations. These are explored and described in Table 1.

The interaction begins at Timestep $T_0 = 0$ when Vehicle M takes its first action. T_0's duration is equal to Vehicle J's Decision Time D_J. The second timestep T_1 begins once Vehicle J takes its action and lasts an amount of time equal to Vehicle M's Decision Time D_M, or after a certain period passes and M may assume J has decided to $wait$. The third timestep T_2 begins when Vehicle M takes its second action. The timesteps T_1 and T_2 are event-based, meaning their durations are tied to the specific values of D_J and D_M in each interaction, respectively.

Vehicle M will accelerate with the appropriate a_{M_1} if it wishes to $block$ Vehicle J's attempt to $join$. This movement is not governed by the GM model. Instead, M will apply the appropriate a_{M_1} so that it would force a collision with J within the lane change manoeuvre duration t_{LC} as follows:

$$a_{M_1} = a_{J_{max}} + 2\frac{s_{M_0} + \left(v_{J_0} - v_{M_0}\right) t_{LC}}{{t_{LC}}^2} \qquad (2)$$

where:

t_{LC} is the lane change duration.

$a_{M_{max}}$ is Vehicle M's maximum acceleration.

a_{M_1} is constrained as follows:

$$\min\left(max\left(a_{M_1}, 0\right), a_{M_{max}}\right)$$

Vehicle M will yield with the appropriate a_{M_1} if it wishes to $allow$ Vehicle J to join ahead by following it. The value of a_{M_1} is derived from Eq. 1 as shown in Table 1 (Eq. 3). Vehicle M will maintain a_{M_1} until it observes an action from Vehicle J or a period of time passes after which M assumes Vehicle J has decided to $wait$.

At the next timestep, if Vehicle J decides to $join$, it employs the appropriate a_{J_2}. This value is governed by the formulae derived from Eq. 1 as shown in Table 1 (Eq. 4). Eq. 4(a) uses the car-leading element of the bi-directional GM model where a leading vehicle adjusts its velocity in response to the velocity of a following vehicle. If Vehicle J decides to $wait$, it continues along its path at a constant speed until M passes (Eq. 5).

The remainder of the interaction is governed in accordance with the general formula in Eq. 1 and subject to the parameters and constraints shown in Table 1 (Equations 1 through 7). The interaction continues until a crash is detected or all the following conditions are met:

- $\left|a_{M_n}\right| \leq 0.01\ m/s^2$
- $\left|a_{J_n}\right| \leq 0.01\ m/s^2$
- $HW_{J_n} \geq HW_{J_{min}}, if\ J^{'}s\ Action = Wait$

The equations of linear motion are used to determine the values of the velocities and distances of each vehicle at every timestep.

Table 1: General Motors car following model parameters and constraints as applied to Eq. 1.

Eq. №	Action	Parameters	Special Cases	Constraints
3	$M: Allow$ or $Follow$	$\Delta s_n = s_{J_n} - s_{M_n}$ $\Delta v_n = \min\left(v_{M_0}, v_{J_n}\right) - v_{M_n}$	$if\ v_{M_n} = 0,\ a_{M_{n+1}} = a_{M_c}$ $if\ HW_{M_n} < HW_{M_{min}},$ $a_{M_{n+1}} = \min\left(a_{M_{n+1}},\ d_{M_c}\right)$	$\min\left(max\left(a_{M_{n+1}}, d_{max}\right), a_{M_c}\right)$
4	$J: Join$	(a) $if\ v_{J_0} < v_{J_D}$: $\Delta s_n = s_{J_n} - s_{M_n}$ $\Delta v_n = \max\left(v_{M_n}, v_{J_D}\right) - v_{J_n}$ (b) $if\ v_{J_0} \geq v_{J_D}$: $\Delta s_n = t_f\ v_{J_n}$ $\Delta v_n = v_{J_D} - v_{J_n}$	-	$if\ v_{J_0} < v_{J_D}$: $\min\left(max\left(a_{J_{n+1}}, 0\right), a_{J_{max}}\right)$ $if\ v_{J_0} \geq v_{J_D}$: $\min\left(max\left(a_{J_{n+1}}, d_{max}\right), a_{J_c}\right)$
5	$J: Wait$	$a_{J_n} = 0$	-	-
6	$M: Punish$	$as\ Follow$	$as\ Follow$ $if\ M\ is\ punitive,\ \propto_M = \propto_P$	$as\ Follow$
7	$M: Ignore$ $/Continue$	$\Delta s_n = t_f\ v_{M_n}$ $\Delta v_n = v_{M_0} - v_{M_n}$	$if\ v_{M_n} = 0,\ a_{M_{n+1}} = a_{M_c}$	$\min\left(max\left(a_{M_{n+1}}, d_{max}\right), a_{M_c}\right)$

where:

d_{max} is the maximum possible deceleration to mitigate collision.

$\min\left(v_{M_0}, v_{J_n}\right)$ (Eq. 3) is used to ensure that the car following model does not push M beyond its initial velocity v_{M_0} even if J has a higher velocity v_{J_0} than v_{M_0}.

$\max\left(v_{M_n}, v_{J_D}\right)$ (Eq. 4) ensures J accelerates to meet its v_{J_D} even if M's velocity is lower than v_{J_D}.

The Δs_n employed in free flow (Eq. 4 and Eq. 7) is equal to the space covered in t_f seconds at the agent vehicle's current velocity (v_{M_n} or v_{J_n}). This creates a "phantom vehicle" which drives t_f seconds ahead for the agent vehicle to follow. This is designed to give a gentle acceleration profile in free-flow situations.

2.3 Communication

Communication in this model is issued by Vehicle M and received by Vehicle J. We employ two forms of communication: *implicit communication*, characterised as the presence and value of acceleration, and *explicit communication*, which is either absent or present. When present, explicit communication can be either positive or negative.

2.4 The Bayesian Elements

Vehicle M is assigned two stochastic properties upon its creation: $attention$ ($attentive/distracted$) and $intention$ ($cooperative/punitive$). Research suggests that 1% of all drivers in the UK were observed using a mobile phone in 2021 (DfT, 2022). In this model, more exaggerated probabilities have been chosen to amplify the effect for easier observation. These base probabilities are known to Vehicle J as *prior beliefs*, therefore we do not expect the general conclusions of this study to be affected by the base values assigned to these probabilities. We confine the purpose of communication to advertise the two stochastic properties of Vehicle M discussed earlier. Vehicle J will use these signals to *update* its beliefs on Vehicle M's stochastic properties in accordance with Bayes' Theorem (Joyce, 2021).

2.5 The Payoff Functions

Ride Comfort U_a

We base ride comfort on both the acceleration values at each timestep (with respect to the comfortable value a_c) and the fluctuation of acceleration across timesteps (best measured as the standard deviation of acceleration about its mean). It is calculated is as:

$$U_a = \frac{1}{T}\sum_{n=1}^{T} \min\left(\left(1-\frac{a_n}{a_c \vee d_c}\right)\times t_n, 0\right) - \sqrt{\frac{1}{T}\sum_{n=1}^{T}(a_n-\overline{a_n})^2} \quad (8)$$

where

a_c is used in the denominator of the first term if $a_n \geq 0$, else d_c.

T is the total count of the interaction's timesteps.

t_n is the duration of timestep n.

Time Headway U_h

U_h is a function of the minimum time headway achieved during the interaction with respect to the minimum acceptable headway HW_{min}.

$$U_h = \begin{cases} U_{crash} & if\ \exists\ HW_{x\in T} \leq 0 \\ \min\limits_{x\in T}\left(1-\frac{HW_{min}}{HW_x}\right) & otherwise \end{cases} \quad (9)$$

Speed difference U_v

For Vehicle M, U_v is based on the difference between the vehicle's initial and final (steady state) velocities. For Vehicle J, U_v is the difference between J's desired velocity and M's final velocity if J opts to $wait$,. If J chooses to $join$, U_v is a function of J's highest achieved velocity.

$$U_{v_M} = 1-\frac{v_{M_0}}{\min\left(v_{M_0}, v_{J_D}\right)} \quad (10)$$

$$U_{v_J} = \begin{cases} 1-\frac{v_{J_D}}{\min\left(v_{M_0}, v_{J_D}\right)} & if\ J\ waits \\ \min\left(1-\frac{\max\limits_{x\in T} v_{J_x}}{\max\left(v_{J_0}, v_{J_D}\right)}, 0\right) & if\ J\ joins \end{cases} \quad (11)$$

Time penalty U_t

Vehicle J is subject to U_t if it chooses to $wait$. U_t is a function of the time J needs to wait for M to pass before it can $join$ behind it. It is calculated as:

$$t_{sum} = \sum_{n=1}^{T} HW_{J_n}\left[HW_{J_n} < HW_{J_{min}}\right]$$

$$t_{extr} = \left(\frac{HW_{J_{min}} v_{J_0} + s_{J_T} - s_{M_T}}{0.5\left(v_{M_0} + \max\left(v_{M_0}, v_{M_T}\right)\right) - v_{J_0}}\right) \quad (12)$$

$$U_{t_J} = \begin{cases} U_{crash}{}^{*} & if\ v_{J_0} \geq v_{M_0} \\ -\mu \times t_{sum} & if\ HW_{J_T} > H \\ -\mu\,(t_{sum} + t_{extr}) & otherwise \end{cases}$$

where

μ is a reduction factor used to normalise U_t with respect to the other payoff components.

* U_{crash} is used in this instance to prevent J from waiting indefinitely for a slower M to pass

Table 2 summarises the payoff calculations based on the action(s) taken.

Table 2: Payoff summary per vehicle per action pair.

Action Pair	Vehicle M	Vehicle J
$Allow/Join$	$U_a + U_h + U_v$	$P(AC) \times (U_{a_{AC}} + U_{h_{AC}} + U_{v_{AC}}) + P(AP) \times (U_{a_{AP}} + U_{h_{AP}} + U_{v_{AP}}) + P(D) \times (U_{a_D} + U_{h_D} + U_{v_D})$
$Block/Join$		
$Allow/Wait$	$U_a + U_v$	$P(AC) \times U_{t_{AC}} + P(AP) \times U_{t_{AP}} + P(D) \times U_{t_D}$
$Block/Wait$		

where

AC: $Attentive\&Cooperative$
AP: $Attentive\&Punitive$
D: $Distracted$

3 EXPERIMENTAL DESIGN

We run three simulation groups as follows:

Control Group. Vehicle M does not engage in any form of explicit communication. Vehicle J relies solely on the base probabilities of Vehicle M's $attention$ and $intention$ as *prior beliefs*. These probabilities are outlined later in this section.

Test Group A. Vehicle M does not issue any explicit signals. Vehicle J reads M's acceleration as an implicit signal to update its *prior beliefs* in line with the likelihoods outlined in Table 6.

Test Group B. Vehicle M employs explicit communication signals as outlined in Table 5.

Each simulation group comprises a simulation of 30,000 interactions. Each interaction is a unique iteration of Vehicle M and Vehicle J with attributes and preferences which are randomly generated from a uniform distribution of preset ranges. All three simulation groups use the same random generator seed. This allows for pairwise comparisons to be made at the interaction level, including paired t-tests.

Table 3 outlines the different attributes and the ranges from which they are generated. Table 4 lists the constants defined in the Method section which are used in all interactions and simulations in this study.

M is assigned the $attentive$ property with a probability $p = 0.75$. This property is concealed from M, i.e. it does not factor into M's decision-making. M is assigned the $cooperative$ property with a probability $q = 0.6$. This property is known to M and factors into its decision-making. M is assigned the $fully\ distracted$ property with a probability $r = 0.5$. This property is also concealed from M.

Vehicle J has *prior* knowledge of these base probabilities, but no concrete knowledge of the attribute assignment. It must assign a probability to each of the three possible positions of Vehicle M on the game tree based on these *prior beliefs.*

Absent any other information, the probabilities J assigns to each of Vehicle M's nodes (Figure 1) are:

- $Attentive/Cooperative$: 0.75×0.6 = 0.45
- $Attentive/Punitive$: 0.75×0.4 = 0.3
- $Distracted$: 0.25

The $distracted$ state lasts for twelve timesteps (5 - 8 seconds, based on the values of D_J and D_M) after which Vehicle M returns to its appropriate actions as described in the Method section.

The entire experiment is conducted twice with two different rulesets. In **Ruleset 1 (Transparent)**, both vehicles enjoy full knowledge of each other's properties (Table 3). Thus, both vehicles have complete information, and the only element of uncertainty comes from the Bayesian elements described previously. In **Ruleset 2 (Blind)**, both vehicles are blind to each other's properties and so have incomplete information. They assume the opponent has identical properties to their own where applicable (otherwise a random value within the ranges specified in Table 3 is used). Both vehicles read each other's velocities and positions accurately.

Table 3: Kinematic properties of the model and their ranges.

Property	Description	Value Range
a_c	Maximum comfortable acceleration	(0.20, 2.00) m/s^2
a_{max}	Maximum allowable acceleration	(2.50, 3.50) m/s^2 (Bokare & Maurya, 2017)
d_c	Maximum comfortable deceleration	(-0.50, -1.50) m/s^2
HW_{min}	Minimum acceptable time headway	(0.50, 3.50) s
DT	Decision time	(0.50, 1.50) s
$\propto_P$	Punitive sensitivity factor (exclusive to M)	(0.15, 0.35)
v_0	Initial velocity	M: (8.00, 18.00) m/s; J: (4.00, 10.00) m/s
s_0	Initial distance ($s_{M_0} = 0$ as datum)	(5.00, 80.00) m
v_D	Desired velocity (exclusive to J)	(0.75, 1.50) × v_{0_J} m/s
ω	$Wait$ penalty reduction factor	(0.10, 0.20)

Table 4: list of constants used in the simulations and their values.

Constant	Description	Value
t_{LC}	Lane change duration	5 seconds (Finnegan & Green, 1990; Salvucci & Liu, 2002)
$\propto_M, m, l$	GM model sensitivity factors	1
t_n	Timestep n (from T_2 onwards)*	0.5 seconds
t_f	*Phantom vehicle* time headway	4 seconds
U_{crash}	Crash penalty	-250
d_{max}	Maximum safe deceleration	-4.5 m/s^2 (AASHTO, 2011; Bokare & Maurya, 2017)

* We set an upper limit of 60 time-based timesteps (t_n) (30 seconds) for the duration of each interaction. The reason for dictating this upper limit is computational efficiency for the computer model.

Table 5: Probabilities of Vehicle M issuing various communicative signals.

Signal Category	Description	Probability of occurrence	
		Attentive	Distracted
Implicit: acceleration	M alters its velocity as appropriate	1	0.5
Explicit: attention e.g. eye contact	M makes eye contact with J	0.9	0.05
Explicit: intention e.g. gestures	M issues a cooperative signal	Cooperative: 0.8; Punitive: 0.2	0.1
	M issues a threatening signal	Cooperative: 0.1; Punitive: 0.8	

Table 6: Breakdown of the likelihoods of each signal given Vehicle M's different possible stochastic attributes.

Signal Category	Value	Description	$P(E\|H)$		
			$Cooperative$	$Punitive$	$Distracted$
Implicit: acceleration	0	J observes no acceleration from M	0.1*	0.1*	0.55
	1	J observes deceleration from M	0.45*	0.3*	0.2
	-1	J observes acceleration from M	0.45*	0.6*	0.25
Explicit: attention e.g. eye contact	0	J is unable to make eye contact with M	0.1	0.1	0.95
	1	J makes eye contact with M	0.9	0.9	0.05
Explicit: intention e.g. gestures	0	J does not observe an intention from M	0.585*	0.415*	0.9
	1	J observes positive intent from M	0.36*	0.09*	0.045
	-1	J observes negative intent from M	0.055*	0.495*	0.055

* These $P(E|H)$ values are based on results obtained from a pilot simulation run of 10,000 interactions.

4 RESULTS

All three simulation groups were concluded successfully. The results are aggregated, and key facts presented in Table 7. The simulations produced logical interaction behaviours. Vehicles behaved in a predictable manner, favouring safer actions, and avoiding unreasonable risks. The number of recorded crashes and near misses was minimal (0.14% and 0.74% at maximum, respectively). The $allow/join$ - $block/wait$ split was balanced, with slight bias towards $block$ / $wait$ (average 44% and 53%, respectively). This indicates a balanced distribution of starting conditions and vehicle attributes. The non-ideal outcomes ($allow/wait$ and $block/join$) were minimal but non-trivial (average 1.6% and 1.1%, respectively).

We pay special attention to the occurrence of non-ideal outcomes in this study, since such outcomes indicate misinterpretation from one or both road users in an interaction, and therefore would prove a useful metric for gauging effective communication between road users. Ruleset 1 produced fewer non-ideal outcomes across all three groups than Ruleset 2. Similarly, Ruleset 1 proved the safer of the two sets, with fewer near misses and crashes than Ruleset 2. Ruleset 1 produced higher average payoffs for both vehicles than Ruleset 2. However, Ruleset 2 saw a higher percent increase for both vehicles' payoffs compared to Ruleset 1.

5 DISCUSSION

Non-ideal outcomes in the form of $allow/wait$ and $block$/join are manifestations of one or more road users misinterpreting an interaction. These outcomes are considered non-ideal since Vehicle M intends a certain outcome, but Vehicle J responds with a different action. Such outcomes typically return worse payoffs to both vehicles than either of the ideal alternatives (average -6.01 and -0.831, respectively). In game theory, such outcomes are considered *Pareto inefficient.* Pareto efficiency is a situation where no player can receive a better payoff without causing another to receive a worse payoff (Osborne, 2003). Since either vehicle could have taken an alternative action to improve at least its own payoff, such outcomes are Pareto inefficient.

In Ruleset 1 (Transparent), the uncertainty around Vehicle M's $attention$ and $intention$ are the main contributors to such outcomes. Since Vehicle M has knowledge of Vehicle J's true attributes, the acceleration value it employs to $allow$ or $block$ Vehicle J is more likely to create an acceptable environment for J. This is why Ruleset 1 produces fewer non-ideal outcomes over all compared to Ruleset 2 (Blind). Furthermore, since Ruleset 1's interaction uncertainty is confined to only two attributes, the effect of communication on Vehicle J's decision making is amplified. This is evident in the total percent decrease in Ruleset 1's non-ideal outcomes which average 28.07%. Ruleset 2's stands at a more conservative 9.63%.

Similarly, Ruleset 1 produces fewer crashes (2 average) and near misses (38 average) than Ruleset 2 (12 and 70, respectively) as there is less room for misinterpretation. In fact, $block/join$ outcomes caused the bulk of crashes and near misses in all three groups. It makes sense therefore that Ruleset 1 sees fewer of these than Ruleset 2, all while enjoying a greater percent decrease in both. Ruleset 1's average percent decrease in crashes and near misses from base to full communication sits at 40.96%, whereas Ruleset 2's averages at only 9.13%. This is partly because Ruleset 2 saw a *rise* in near misses in the test groups over the control (17.46%). This suggests that communication encouraged Vehicle J to take more risks. Interestingly, however, despite the increase in near misses, there was a 35.71% reduction in crashes. Active communication, it seems, has encouraged Vehicle J to take more $calculated$ risks, whilst also refraining from taking potentially catastrophic risks. Indeed, looking at average payoffs, we see further evidence to corroborate this theory.

The average payoffs for both M and J are predictably higher (better) in Ruleset 1 than Ruleset 2 (-0.668 vs -0.993). Having full knowledge of an opponent's attributes and preferences means both vehicles can make accurate calculations on each other's movements and responses, resulting in fewer over-all dangerous or undesirable interactions. Both rulesets benefit from added communication. The main difference is that Ruleset 1 saw the most benefit going from no communication to implicit communication, whereas Ruleset 2 saw the most benefit going from implicit to full communication. Since players under Ruleset 1 already play an optimised game in which they have near-complete information, implicit communication is sufficient to provide Vehicle J meaningful certainty on M's $attention$ and $intention$. Further communication (Group B) only serves to strengthen what is already sufficiently known. On the other hand, when the information available is either incomplete or inaccurate, such as in Ruleset 2, explicit communication becomes more vital as information becomes more limited. Indeed, research shows that

Table 7: Summary of simulation results.

Metric	Ruleset 1 (Transparent)			Ruleset 2 (Blind)		
	None (Control)	**Implicit (Group A)**	**Full (Group B)**	**None (Control)**	**Implicit (Group A)**	**Full (Group B)**
Allow/Wait	162	166	119	191	193	166
Block/Go	81	64	57	167	153	156
Total near misses	47	35	32	63	74	74
Total crashes	2	1	1	14	12	9
Average payoff (Vehicle M)	-0.776	-0.735	-0.731	-1.154	-1.085	-1.017
One-tailed paired t-test (vs Implicit)	-	< 0.01	0.31	-	0.02	< 0.01
One-tailed paired t-test **(vs None)**	-	-	**< 0.01**	-	-	**< 0.01**
Average payoff (Vehicle J)	-0.619	-0.580	-0.569	-0.967	-0.909	-0.827
One-tailed paired t-test (vs Implicit)	-	< 0.01	0.11	-	0.04	< 0.01
One-tailed paired t-test **(vs None)**	-	-	**< 0.01**	-	-	**< 0.01**

road users seek communication from others when facing uncertainty (Portouli et al., 2014). Our results corroborate these findings.

Finally, communication in both rulesets gave statistically significant payoff improvements to both Vehicle M (the issuer) and Vehicle J (the recipient). Thus, cooperative communication can emerge from selfish motives. These improvements were also statistically significant with implicit communication over control, meaning that active participation by Vehicle M was not necessary for Vehicle J to make better decisions based on implicitly communicated information. This is an important finding considering autonomous vehicles, which may be able to make use of freely advertised information such as acceleration to better understand human drivers' intent.

6 CONCLUSIONS

We have conducted a series of experiments which demonstrate that non-cooperative game theory is a viable framework to study, model and characterise the exchange of implicit and explicit communication between interacting road users. More importantly, we show that it is possible to produce meaningfully safer interactions and fewer non-ideal outcomes without the need to assume common goals *a priori*. By foregoing this assumption, non-cooperative game theory provides a more robust framework for modelling communication descriptively and prescriptively in a variety of situations and scenarios. Therefore, in a strict game-theoretic sense, effective communication is a viable non-cooperative strategy which can benefit both the sender and the recipient.

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