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How Can Autonomous Road Vehicles Coexist with Human-Driven Vehicles? An Evolutionary-Game-Theoretic Perspective

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Abstract: The advent of highly automated vehicles in the form of autonomous road vehicles (ARVs) is bound to bring about a paradigm shift in road user interaction, especially that between ARVs and human-driven vehicles (HDVs). Previous literature on the game-theoretic interaction between ARVs and HDVs tends to focus on working out the best possible strategy for a single interaction, i.e. the Nash equilibrium. This position paper sets out to demonstrate the importance and potential impact of applying evolutionary game theoretic principles to what is effectively a dynamic population driven by evolutionary forces – the population of road users. We demonstrate using theoretical scenarios that simply maintaining Nash equilibria does not guarantee evolutionary success. Instead, ARVs must enjoy a demonstrable advantage over other road users when few in numbers. Otherwise, their uptake will slow down and eventually reverse. We argue that the same selection factors which influence the success of living populations in the natural world also influence the success of the different vehicle types and driving styles in the road user population, including ARVs. We demonstrate this by assigning an expected fitness score to each vehicle in a one-to-one interaction, such as at a junction. This fitness score is dependent on driver, rider and economic costs incurred by the vehicle and/or its occupant(s) during interaction. In turn we show that ARV and transport system designers need to ensure that the fitness score of their systems create evolutionary stability.

1 INTRODUCTION

Road transport is a highly interactive activity in which road users must compete for space and priority. This is done through a vast array of competitive, cooperative, and communicative behaviours in which road users engage to facilitate their distribution in space and time. These behaviours are defined as road user interactions (Markkula et al., 2020). As autonomous road vehicles (ARV) reach market maturity and begin using the road network, their interaction with human-driven vehicles (HDV) will strongly influence the success of ARVs in the short and long term. In this position paper, we argue that this extends beyond the one-on-one interaction between ARVs and HDVs to include the population-level interaction between the two distinct groups of road users, each with their own inherent properties.

There are fundamental differences between ARVs and HDVs that set them apart as distinct road user populations. These differences include differences in the decision-making mechanism (Elvik, 2014; Fox et al., 2018; Harris, 2017; Kang & Rakha, 2020; Meng, Su, Liu, & Chen, 2016), attention span, driving behaviour (Millard-Ball, 2018; van Loon & Martens, 2015) and over-all communication and interaction capabilities (C. Liu, Lin, Shiraishi, & Tomizuka, 2018). Many researchers believe that HDVs and human road users in general are likely to learn the nuances of ARV behaviour and subsequently take advantage of them to force ARVs to yield at every interaction (Cooper et al., 2019; Fox et al., 2018; Millard-Ball, 2018). Indeed, experiments on humans and AI have demonstrated that whilst humans expect cooperative behaviour from machines, they are rarely willing to reciprocate (Karpus, Krüger, Verba, Bahrami, & Deroy, 2021). If

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ARVs are pushed to yield at most interactions, they will be unable to make significant progress on the road network (Cooper et al., 2019; Fox et al., 2018; Millard-Ball, 2018). This would in turn cause significant traffic safety and efficiency issues and damage the uptake of ARVs.

Various solutions have been proposed in the literature, including building larger, more imposing ARVs or mounting loud sirens or water pistols to "punish" transgressors (Fox et al., 2018). Going further, some suggested programming ARVs with a non-zero probability to cause collision as a form of credible threat to dissuade would-be exploiters (Camara, Dickinson, Merat, & Fox, 2019). Others have programmed a Stackelberg game in which the bullied virtual ARV actively punishes the human player if they behaved antisocially in previous interactions (Cooper et al., 2019). Setting aside their ethical and practical ramifications, such measures merely offer reactionary solutions to a fundamental problem and are unlikely to work in the long term.

Instead, one must look to other environments in which we can observe competition and cooperation between fundamentally different populations. One such environment is the natural world. There, members of different animal species (and within the same species) interact, compete, and cooperate with each other to share limited resources. Such resources include food, shelter, and mates. These are resources each individual needs to maximise its own fitness and ensure survival and reproduction. Yet, despite the prevalent scarcity of these resources in most natural settings, cooperative behaviour is widely spread in animal populations and fatal conflicts are rare outside of predation (J. Maynard Smith & Price, 1973; Wilkinson, 1984).

Animal cooperation in nature can evolve and persist through means of natural selection (Hamilton, 1964). Evolutionary game theory provides the ideal theoretical framework for understanding the dynamics that lead to the evolution of cooperation (Bendor & Swistak, 1995; John Maynard Smith, 1982). Once evolved, cooperation persists through means of evolutionary stability. Evolutionary stability is a state in which most or all members of a population of individuals interact in a way where a new, small group of mutant individuals cannot invade and dominate the population (John Maynard Smith, 1982). A set of behaviours that fits this description is known as an evolutionarily stable strategy (ESS).

ESSs have been used to describe emergent cooperative and competitive behaviours in animal populations (Sirot, 2000; Wilkinson, 1984). The classic Hawk-Dove game provides a conceptual illustration of the evolution of cooperation (J. Maynard Smith & Price, 1973). Many animal behaviours in nature have been shown to conform to the categorical paradigm of Hawk-Dove games. Examples include nesting habits of digger wasps (Brockmann, Grafen, & Dawkins, 1979), food sharing in vampire bats (Wilkinson, 1984) and territorial conflicts in funnel web spiders (Hammerstein & Riechert, 1988).

Beyond the natural world, several studies exist on the applicability of ESSs in other disciplines. One such example is the work of Altman, El-Azouzi, Hayel, and Tembine (2009) who use a variant of the Hawk-Dove game to predict the success and evolutionary stability of different Internet transport protocols (TCPs) and provide guidelines for the introduction and upgrade of evolutionarily-stable TCPs. Other such studies exist in the fields of economics (Friedman, 1991; Kandori, 1996), policy making (da Silva Rocha & Salomão, 2019; Xu, Wang, Wang, & Ding, 2019) and stakeholder conflict (L. Liu, Zhu, & Guo, 2020; Yu, Zhao, Huang, & Yang, 2020).

Several studies have also been conducted in the field of transport. Some applications include route and mode choice modelling (Lei & Gao, 2019; Wu, Pei, & Gao, 2015). Others have used evolutionary game theory as a predictor and facilitator of effective implementation of government subsidies and compliance monitoring in transport. Examples include new-energy vehicles (Wang, Fan, Zhao, & Wu, 2015) and public transport (Zhang, Long, Huang, Li, & Wei, 2020). Some road user interaction models have also made use of evolutionary game theory to predict driver attention, simulate driver cooperation and address social dilemmas (Chatterjee & Davis, 2013; Iwamura & Tanimoto, 2018). One exploratory study has investigated the aggressiveness of driving behaviour from a Hawk-Dove standpoint (Free, 2018). To the authors' knowledge, however, this concept is yet to be expanded to draw larger-scale conclusions on the evolutionary stability of road user populations. More specifically, evolutionary game theory has not yet been used as a framework for ARVs' interaction with HDVs.

2 CONCEPTUAL DEMONSTRATION

There are parallels to be drawn between the competition for resources in nature and the interaction between vehicles on the road network. Whilst animals in nature compete for food, territory and mates, vehicles (both human-driven and autonomous) compete for road space and priority on the road network. In both worlds, competitors can either cooperate to share the contested resource or expend energy fighting for it. Only the "fittest" individuals will succeed in reproduction and proliferation. This fitness can be loosely defined by the individual's success in securing a viable amount of the contested resources without compromising one's viability. Thus, the use of the concept of fitness ensures that strategies adopted do not endanger the safety of the agent (and by extension, its opponent). This is crucial for ARVs since one of the main motivations for their development is the elimination of human-related safety risks. In terms of reproduction, animals reproduce genetically via procreation, whereas vehicles and driving styles "reproduce" *memetically* (Dawkins, 2016) through increased sales and imitation, respectively. This parallel is possible because as far as behaviour is concerned, an ARV is a living organism, whose goal is to "reproduce" through selling more models (copies) of itself, which it can achieve by being successful in the road space and enticing potential customers to buy in.

Game-theoretic ARV models in the literature are often validated against opponents playing by the same rules (Kang & Rakha, 2020; Meng et al., 2016) In reality, such results are only valid against a static, homogenous population. The road user population, however, is dynamic, varied and constantly evolving. More importantly, road users have the capacity to adjust their behaviour based on the characteristics of their opponents. This is known as a conditional strategy in game theory (Gross & Repka, 1998). We envisage that, unlike model simulations in the literature, HDVs will react to the introduction of ARVs by adjusting their behaviour to maximise their benefit. Primarily, HDVs will look to exploit ARVs' propensity to be risk averse and their ability to maintain permanent rationality and attention. Unless ARVs can adapt in turn, they risk developing strategies that are evolutionarily unstable and thus fail in penetrating the population of road users.

2.1 Theoretical Formulation

As ARVs mature and make their way to the market, they will begin their entry into the road user population gradually. These ARVs will likely operate within a connected environment in which ARV-ARV interactions are concluded more efficiently and effectively (Hancock, Nourbakhsh, & Stewart, 2019; Wadud, MacKenzie, & Leiby, 2016).

As with the traditional Hawk-Dove game, vehicles interact to share road space. Interaction costs energy. Conceptually, there are three elements to an interaction cost function: the *economic* costs (fuel consumption, tyre wear, etc.), the *driver* costs (increased demand on attention, planning, decision-making, etc.) and the *rider* costs (safety, delay, ride comfort, etc.). All costs traditionally apply to an HDV. In contrast, ARVs arguably bear no driver costs since ARV controllers are expected to be ever-attentive and ever-processing. Thus, it makes no difference to an ARV whether an interaction is required and to what level of sophistication.

There are two key concepts to understand in how vehicle interactions are represented in this paper. Vehicles can either choose to *facilitate* an interaction (Dove-like behaviour) or *escalate* in a bid to win priority (Hawk-like behaviour). Facilitation can be thought of as cooperation between the two vehicles to conclude the interaction with the maximum (Pareto efficient) payoff for both vehicles. Escalation, on the other hand, constitutes competitive behaviour whose aim is to maximise individual payoff at the expense of the other vehicle. Therefore, if both vehicles choose to facilitate, they interact to share priority equitably, i.e., it goes to the vehicle which, by convention, has right of way. We assume that, on average, a vehicle would have right of way half of the time. This is conceptualised as an interaction reward $R = 0.5$. If one vehicle escalates and the other facilitates, the escalating vehicle forcibly takes priority ($R = 1$). If both escalate, both vehicles attempt to forcibly win priority, expending considerable energy in the process, but will determine priority by convention in the end ($R = 0.5$). Facilitation incurs the least interaction cost (C), typically thought of as the mere cost of engaging in an interaction with another vehicle. Escalation incurs greater cost as that would likely involve aggressive manoeuvring or excessive acceleration. Mutual escalation incurs the greatest cost as both vehicles are assumed to maintain their escalation for longer. Table 1 below demonstrates the concepts discussed.

Table 1: Normal-form the road user interaction game.

Veh 2 Veh 1	Facilitate (F)	Escalate (E)
Facilitate (F)	0.5 - C_{FF}, 0.5 - C_{FF}	0 - C_{FE}, 1 - C_{EF}
Escalate (E)	1 - C_{EF}, 0 - C_{FE}	0.5 - C_{EE}, 0.5 - C_{EE}

$$C_{FF} = C_{FE} < C_{EF} < C_{EE}$$

John Maynard Smith (1982) established two conditions that a strategy must meet in order to be evolutionarily stable. For a resident strategy, this means the ability to resist invasion by new strategies. For a new strategy, this means the ability to invade a population of resident strategies.

- The subject strategy must do better against itself than any other strategy could
- If a strategy exists which could do equally well against the subject strategy, the subject strategy must do better against the other strategy than the other strategy could against itself

This can be mathematically expressed as follows

$$E(S_i, S_i) > E(S_j, S_i) \text{ OR} \tag{1}$$

$$\begin{gathered} E(S_i, S_i) = E(S_j, S_i) \text{ AND} \\ E(S_i, S_j) > E(S_j, S_j) \end{gathered} \tag{2}$$

where

S_i, S_j are the subject strategy and the set of all other strategies, respectively

$E(S_i, S_j)$ is the total expected payoff for S_i against S_j

These broad conditions can be adapted and applied to the situation where ARVs are introduced to the market. The current resident population in the road network is that of HDVs. As of 2022, they comprise well over 99% of all vehicular road traffic. Therefore, any new fleet of ARVs which wish to establish a meaningful foothold in the road user network must satisfy one of the below two conditions

$$E(S_{ARV}, S_{ARV}) > E(S_{HDV}, S_{ARV}) \text{ OR} \tag{3}$$

$$\begin{gathered} E(S_{ARV}, S_{ARV}) = E(S_{HDV}, S_{ARV}) \text{ AND} \\ E(S_{ARV}, S_{HDV}) > E(S_{HDV}, S_{HDV}) \end{gathered} \tag{4}$$

where

S_{ARV}, S_{HDV} are the interaction strategy sets available to ARVs and HDVs, respectively

$E(S_x, S_y)$ is the total expected payoff for each strategy in Strategy Set x against each strategy in Strategy Set y and can be calculated as follows

$$E(S_x, S_y) = \sum_{i=1}^{n} u(i) \times \sigma(i) \tag{5}$$

where

$i \in \{1, 2, 3, \ldots, n\}$ is an outcome of the normal-form game between Strategy Sets S_x and S_y

$u(i)$ is the utility (payoff) of Outcome i, which is calculated as $R - C$

$\sigma(i)$ is the probability of Outcome i

Looking back at Table 1, i in this scenario can be one of four outcomes: $i \in \{FF, FE, EF, EE\}$. As such, the total expected payoff for ARVs can be thought of as the weighted sum of the ARV payoff of each of these four outcomes weighted against each outcome's probability. This probability will depend on the strategy employed by both ARVs and HDVs.

Substituting Equation 5 into the inequalities in 3 and 4 yields the following inequalities

$$\sum_{i=1}^{4} (R_i - C_i) \times \sigma(i) > \sum_{j=1}^{4} (R_j - C_j) \times \sigma(j) \tag{6}$$

where

$i \in \{FF, FE, EF, EE\}$ is an outcome of the game between Strategy Sets S_{ARV} and S_{ARV}

$j \in \{FF, FE, EF, EE\}$ is an outcome of the game between Strategy Sets S_{HDV} and S_{ARV}

$$\begin{gathered} \sum_{i=1}^{4} (R_i - C_i) \times \sigma(i) > \sum_{j=1}^{4} (R_j - C_j) \times \sigma(j) \\ \text{AND} \\ \sum_{k=1}^{4} (R_k - C_k) \times \sigma(k) > \sum_{l=1}^{4} (R_l - C_l) \times \sigma(l) \end{gathered} \tag{7}$$

where

$k \in \{FF, FE, EF, EE\}$ is an outcome of the game between Strategy Sets S_{ARV} and S_{HDV}

$l \in \{FF, FE, EF, EE\}$ is an outcome of the game between Strategy Sets S_{HDV} and S_{HDV}

Fulfilling the inequalities in 6 and 7 require the optimisation of three variables

- Maximisation of R_i/R_k
- Minimisation of C_i/C_k
- Maximisation of $\sigma(i)/\sigma(k)$ where $R_i - C_i/R_k - C_k$ is at a maximum

The solution(s) to this optimisation problem will vary greatly in the real world based on ARV application, the driving culture of the local existing road user population, traffic rules and regulations, and other considerations. However, the approaches available to implement such solutions can generally be grouped into three categories.

- External measures to provide greater incentive for customers to adopt ARVs
- Capitalisation on inherent ARV behavioural, computational, and sensory strengths
- Creation of a cooperative ARV subcommunity where ARVs work together to maximise the subcommunity's over-all fitness

In the following section, we provide an example of how some of these categorical solutions can be used to optimise the problem.

Table 2: Reward and cost parameters for road user interaction demonstration.

	ARV				HDV			
	C_{FF}	C_{FE}	C_{EF}	C_{EE}	C_{FF}	C_{FE}	C_{EF}	C_{EE}
	0.2	0.2	0.55	0.85	0.3	0.3	0.65	1.05
	R_{FF}	R_{FE}	R_{EF}	R_{EE}	R_{FF}	R_{FE}	R_{EF}	R_{EE}
vs ARV	0.5	0	1	0.5	0.5	0	1	0.8
vs HDV	0.5	0	1	0.2	0.5	0	1	0.5

2.2 Demonstrative Example

We continue with the set-up described in Section 2.1 with an initial introduction of a small population of ARVs. Table 2 gives an overview of the chosen parameters which correspond to the different costs and rewards associated with vehicle interaction.

These values are simplified to illustrate the concept of evolutionary stability. In the real world, the parameters would be subject to a range of traffic, policy, vehicle, and human factors which would together make up the cost and reward functions.

The cost parameters outlined in Table 2 for ARVs are lower than the cost parameters for HDVs. This is to account for the fact that ARVs bear no driver costs associated with the interaction. Hence, the over-all cost for interacting with other vehicles is smaller.

Table 3: Normal-form of the ARV-ARV game (top), HDV-HDV game (middle) and HDV-ARV game (bottom). Fractions under actions denote each action's probability based on the game's Nash equilibrium.

ARV 2 / ARV 1	F 0.5	E 0.5
F 0.5	0.3, 0.3	-0.2, 0.45
E 0.5	0.45, -0.2	-0.35, -0.35

HDV 2 / HDV 1	F 0.5	E 0.5
F 0.5	0.1, 0.1	-0.4, 0.35
E 0.5	0.35, -0.4	-0.65, -0.65

ARV / HDV	F 1	E 0
F 0	0.1, 0.3	-0.4, 0.45
E 1	0.35, -0.2	-0.35, -0.65

The reward parameter for mutual escalation for HDVs (R_{EE}) has been increased from 0.5 (equal distribution of priority) to 0.8 (80-20 distribution of priority to HDVs' benefit). The reason for this is that this scenario echoes the research findings discussed in the introduction with regards to HDVs taking advantage of and pushing ARVs to yield at most interactions. The result of this asymmetry creates a game matrix in which HDVs' best strategy against ARVs is to escalate with 100% probability. In turn, this pushes ARVs to adopt a 100% probability to facilitate. This creates a unique Nash equilibrium in HDV-ARV interactions of EF. Table 3 illustrates this in normal form.

HDVs' exploitation of ARVs puts ARVs at an immediate disadvantage. This is clearly demonstrated in Figure 1, which illustrates the average expected payoff profile for each of the two populations across all possible proportions of ARVs out of the entire population.

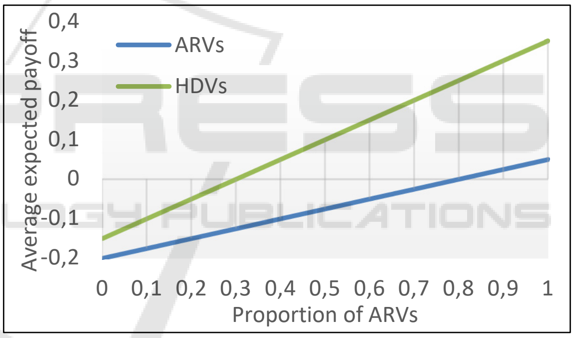

Figure 1: Average expected payoff profile for ARVs and HDVs under the conditions set out in Table 3.

Under the currently set circumstances, HDVs enjoy a significant advantage over ARVs across the board. At lower proportions, ARVs receive the least possible expected payoff. This will result in ARVs failing to enter the road user population. Using the figures in Table 3, we can calculate the total expected payoff for each strategy pair at $pARV = 0$ as follows

$E(S_{ARV}, S_{ARV}) = 0.05$ $E(S_{HDV}, S_{ARV}) = 0.35$
$E(S_{ARV}, S_{HDV}) = -0.2$ $E(S_{HDV}, S_{HDV}) = -0.15$

Therefore

$$E(S_{HDV}, S_{HDV}) > E(S_{ARV}, S_{HDV})$$

Which means that the current set of HDV strategies is evolutionarily stable, thus ARVs will not be able to invade the population.

To combat this, we introduce two measures inspired by the three solution categories outlined in

Section 2.1. Namely, we allow ARVs to communicate with each other via V2V channels. This allows ARVs to adopt a 100% probability to facilitate when interacting with one another, thus maximising the payoff for both vehicles (Pareto efficient). Second, we introduce a subsidy function which offsets the economic costs of operating an ARV. Subsidies can take many different forms and have varying effects on both ARVs and HDVs in the target population. Evolutionary game theory has already been used to model the likely reaction of new-energy car manufacturers to government subsidies and penalties (Zhang et al., 2020). In this paper, we focus on modelling the *effect* of a hypothetical subsidy on the over-all fitness of ARVs in the population. The subsidy is granted in a manner that is inversely proportional to the proportion of ARVs in the population so that maximum subsidy is given when ARV population is at a minimum. Equation 8 illustrates how the subsidy is applied in this example.

$$\widehat{C_E} = C_E(1 - Q \times pARV) \quad (8)$$

where

C_E is the ARV's economic cost of interaction

$\widehat{C_E}$ is the ARV's economic cost of interaction after subsidy

$pARV$ is the proportion of ARVs in the population

Q is a constant which determines the magnitude of the subsidy and its effect on the given cost. For example, a Q equal to C_E offsets the entire economic cost of interaction at $pARV = 0$

We choose a Q value of 0.75, which provides a net economic benefit (incentive) to ARVs. The subsidy is terminated once the ARV proportion reaches one half ($pARV = 0.5$). The resultant change in normal-form payoffs is shown in Table 4.

Figure 2 illustrates the average expected payoff profile for each of the two populations following the application of the two measures.

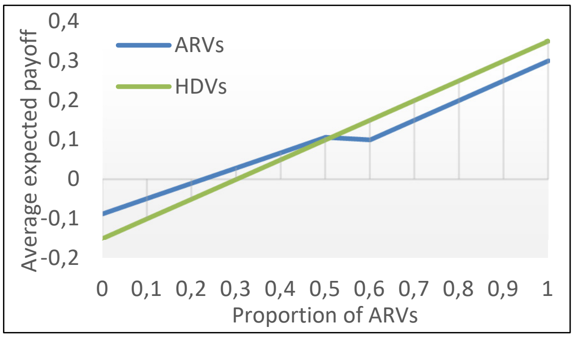

Figure 2: Average expected payoff profile for ARVs and HDVs under the conditions set out in Table 4.

Table 4: Normal-form of the ARV-ARV game (top), HDV-HDV game (middle) and HDV-ARV game (bottom) after applying V2V communication and government subsidy. Fractions under actions denote each action's probability based on the game's Nash equilibrium.

ARV 2 ARV 1	F 1	E 0
F 1	0.413, 0.413	-0.09, 0.75
E 0	0.75, -0.09	0.1, 0.1

HDV 2 HDV 1	F 0.5	E 0.5
F 0.5	0.1, 0.1	-04., 0.35
E 0.5	0.35, -0.4	-0.65, -0.65

ARV HDV	F 1	E 0
F 0	0.1, 0.413	-0.4, 0.75
E 1	0.35, -0.09	-0.35, -0.2

The application of V2V communication has the positive effect of improving the average expected payoff for ARVs as their numbers grow. This helps close the gap between ARVs and HDVs in terms of over-all fitness. Applying the subsidy has the added benefit of offsetting some of the costs incurred by ARVs. This in turn offsets the average expected payoff for ARVs to levels above that of HDVs across the population proportion to which a subsidy applies.

Using the figures in Table 4, we can calculate the total expected payoff for each strategy pair at $pARV = 0$ as follows

$E(S_{ARV}, S_{ARV}) = 0.41$ $\quad E(S_{HDV}, S_{ARV}) = 0.35$
$E(S_{ARV}, S_{HDV}) = -0.09$ $\quad E(S_{HDV}, S_{HDV}) = -0.15$

Therefore

$$E(S_{ARV}, S_{ARV}) > E(S_{HDV}, S_{ARV})$$

Which means that the new set of ARV strategies is evolutionarily stable, thus ARVs will be able to invade the population and reach an evolutionarily stable state at the population proportion at which the average expected payoff of ARVs equals that of HDVs. This can be graphically identified in Figure 2 as the point of intersection between the two curves, at approximately $pARV = 0.5$.

3 CONCLUSIONS

The relationship between ARVs and HDVs is a complex, dynamic, and evolving one. Evolutionary game theory gives us a nature-based understanding of a living, constantly evolving population: the population of road users. Members of this population interact with one another and compete for the finite resources of space and priority. A vehicle or driving style's over-all performance in the daily task of interactive driving dictates whether it continues to be adopted or gets dropped in favour of an alternative. This process of *memetic* reproduction is analogous to genetic reproduction (Dawkins, 2016). Therefore, without proper understanding of the evolutionary dynamics of this population, ARV manufacturers and policymakers may find that their ARVs are unable to keep a meaningful presence within the road user population. Cooperative behaviour between selfish individuals in the natural world can only be adequately explained using evolutionary game theory (John Maynard Smith, 1982; J. Maynard Smith & Price, 1973). Similarly, we argue that cooperative behaviour in a naturally evolving road user population with autonomous entities can only be ensured if these entities are programmed in line with the principles of evolutionary game theory.

The fitness and therefore success of ARVs is governed by a cost and reward function. The particulars of such a function vary greatly and depend on the class of ARV in question, the prevalent driving culture and road etiquette, and the traffic rules and policies in place. For example, heavy goods vehicles will skew considerably towards faster, more efficient transport, whilst passenger vehicles may be more sensitive to passenger comfort and satisfaction. The values used in the examples described in this paper have been chosen to demonstrate how the dynamic *may* look under certain conditions and behavioural patterns. However, if the road user population were to behave differently or the network conditions be different, it is highly probable that the resulting dynamic will not produce evolutionarily stable outcomes that allow for a viable ARV sub-population. The topic of characterising and tuning the reward and cost functions of ARVs is a subject that requires further research.

Future research will investigate developing a methodology by which ARVs can dynamically adapt to changes in policy, HDV strategies, and other factors to ensure evolutionary stability is maintained throughout the course of ARV introduction and beyond.

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